Market Structure and Profit Complementarity: The Case of SPECT and PET *

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Abstract

The paper examines how the market structure in which a firm operates affects complementarity in its decisions to adopt service-oriented technologies. Adoption decisions over multiple technologies often exhibit interdependence and the competitive environment in which a firm operates can substantially affect such interdependence. We use the case of hospital adoption of SPECT and PET diagnostic imaging technologies to illustrate the effects of market structure on profit complementarity between decisions. A monopolist hospital faces strong cannibalization of SPECT service utilization by adopting PET as well. With one or more competing hospitals in the market for SPECT service, the potential for self-cannibalization diminishes, and hence we would expect complementarity to increase.

We test for changes in profit complementarity between the adoption of SPECT and PET technologies using a static discrete choice framework that accounts for the strategic nature of adoption among market rivals. Specifically, we use observed variation in joint versus separate adoption of the two technologies across rival adoption strategies to infer changes in the relative profitability of joint versus separate adoption. We account for the endogeneity of a rival hospital's adoption decisions using a recursive approach based on alternating parameter estimation and equilibrium solution. We find evidence that hospitals in more competitive hospital markets face greater profit complementarity between their adoption decisions; however, the primary motivation for adopting these technologies appears to be patient feeding rather than direct service profit maximization. We discuss implications for inference about technology adoption in strategic settings. In particular, we argue that neglecting variation in profit complementarity across market structures can result in biased estimates, even when only the adoption of one technology is of interest.

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1 Introduction

This paper examines firm adoption decisions over multiple, service-oriented technologies that are crucially tied to the firm's participation in related service markets. We focus on the interaction of hospitals' decisions to adopt single-photon emission tomography (SPECT) and positron emission tomography (PET) and how hospital market structure affects this interaction. With both diagnostic imaging technologies, one can view the adoption decision as synonymous with the decision to enter the associated service market. Hence, the market forces that affect the profitability of each service also influence the adoption payoffs. Importantly, the manner in which the profitability of the two services interacts gives rise to complementarity or anti-complementarity between the two adoption decisions. Market conditions will affect the interaction in profits between the two services and hence the complementarity between the adoption decisions. In this manner, the case of SPECT and PET illustrates how market structure influences the degree of complementarity among a firm's decisions.

The substitutability of SPECT and PET scans for most consumers will drive down the complementarity between a monopolist hospital's decisions to adopt the technologies, even when we allow the hospital to price discriminate. The downward pressure on complementarity stems from the presence of one service cannibalizing usage of the other. If a competing hospital adopts SPECT technology and offers scanning services, then its presence in the SPECT submarket will draw away some of those SPECT consumers that a monopolist would otherwise lose by offering PET as well. Hence, we expect that the source of anti-complementarity faced by the hospital should weaken as one of the submarkets becomes more competitive.

We test this intuition empirically with a discrete choice framework that takes into account both the interaction between the two adoption decisions and the interaction among competing hospitals in a market. We model the adoption decisions as a choice over bundles of the two technologies, using an approach similar to Gentzkow (2005) in his work on print and online newspapers. To incorporate the strategic considerations, we employ the Nested Pseudo-Likelihood (NPL) method developed by Aguirregabiria and Mira (2004). The results of the structural estimation suggest that profit complementarity is affected by the number of hospitals in the market, rather than expectations regarding rival adoption. In the end, the estimated parameters provide stronger evidence for patient-feeding as the motive for adopting these technologies, rather than direct service profit maximization.

Multi-product oligopolies present distinct challenges to the study of imperfect competition, both in its theoretical and empirical branches. Researchers confront the dilemma that there are very few firms that make decisions with consideration of only one product; however, the multi-product nature of most firms adds considerable complexity to our models, especially when strategic factors are present. When the product line of a multi-product firm is linked to its technological adoption decisions, the same strategic considerations that affect the firm's product choices also affect these adoption decisions. In such situations, the market environment will have an impact not only on the profitability of each adoption decision in isolation, but also on the interaction of the decisions in the firm's overall profits.

Several important factors complicate the decision problem of a multi-product firm relative to that of a single-product firm. A firm offering multiple products that consumers view as substitutes faces the prospect of cannibalization of its revenues in one submarket through its operation in another. If the firm enjoys enough market power, it may partially, and in some cases completely, ameliorate such cannibalization through price discrimination. Of course, if consumers view the products offered by the firm as complements, then the firm's operation in one submarket may expand demand in others. Furthermore, products may also interact in production, generating economies or diseconomies of scope.

The notion of profit complementarity is a cumulative measure of the these various effects. Demand-side complementary products and economies of scope will generate positive profit complementarity, whereas demand-side substitution and diseconomies of scope will generate negative profit complementarity. The precise definition of profit complementarity would vary by context; however, for a dual technology adoption situation like that under study, it suffices to define the two adoption choices as profit complements if adoption of one technology increases the profitability of adopting the other *ceteris paribus*.[1] This definition corresponds to strategic complementarity among the components of a firm's own strategy. Note that we use the term *negative profit complementarity*, or *anti-complementarity*, for the opposite case, rather than *profit substitutability*.

The use of profit complementarity to aggregate cost and demand factors is well-suited to contexts where the econometrician observes limited information about the post-adoption play among market rivals. In the empirical investigation, we use a strategic discrete choice model to infer changes in profit complementarity between adoption decisions over market structure. While we do not observe data on the prices, quantities, or profits that result from the post-adoption competition, the observed adoption decisions, along with data on hospitals and markets, provide insight into how market conditions affect profit complementarity between SPECT and PET adoption.

The market forces that drive the adoption of technologies and the selection of services provided by hospitals has attracted a great deal of attention over the last several decades. Given the critical importance of the hospital services sector to the economy, the relative availability of data pertaining to this sector, and the host of intriguing economic phenomena that appear, the level of interest comes as no surprise. Along with the bundle of issues specific to the industry, such as the medical arms race, physician-induced demand, and third-party payment, the hospital services industry provides insights into broader questions of imperfect competition. In particular, the variety of interacting services supplied by a given hospital presents an application and test of models of multi-product oligopoly.

Among the many services provided by hospitals, diagnostic imaging services are among the most technologically intensive. This feature, combined with the relative availability of data on markets for these services, has led to a number of empirical investigations on the role of competitive factors in technological choice that have focused on these markets. The works of Trajtenberg (1989), Baker (2001), and Schmidt-Dengler (2005) exemplify the types of questions that economists have tried to address by examining diagnostic imaging technologies. Trajtenberg (1989) examines the market for computed tomography (CT) scanners to discern the welfare gains from the diffusion of product innovations using discrete choice analysis of hospital purchase decisions. Baker (2001) and Schmidt-Dengler (2005) study a dynamic model of the timing of adoption of magnetic resonance imaging (MRI) by hospitals. While Baker (2001) investigates the effect of HMO penetration on diffusion of the technology into markets, Schmidt-Dengler (2005) focuses on strategic factors stemming from the oligopoly structure of most hospital markets.

The difference in the present study from these earlier works extends beyond the particular choice of diagnostic scanner. The lack of detailed purchase data does not permit the evaluation of these technologies from a welfare perspective as Trajtenberg (1989) does.

[1] A more general definition of profit complementarity (or better yet, *payoff* complementarity) between two choice variables would be that the objective function be supermodular (for positive profit complementarity) or submodular (for negative profit complementarity) in those variables. See Milgrom and Roberts (1990b) for formalization and discussion of this concept.

Instead, this paper, like those of Baker (2001) and Schmidt-Dengler (2005), concentrates on the market factors that affect hospital's decisions to adopt these technologies. However, unlike these papers, we focus on the complementarity of multiple adoption decisions, rather than on the timing of a single adoption. We certainly do not claim that adoption timing is not important; rather, we highlight another feature present in these contexts. In this respect, the present study complements the previous literature. Ideally, one should consider both adoption timing and complementarity because each has implications for the other. We neglect the dynamic considerations present mainly for simplicity.

The remainder of the paper proceeds as follows. We first present an analytical framework for the effects of market structure on profit complementarity. We then illustrate how the nature of competition among rivals may affect profit complementarity between adoption decisions. Turning to our empirical context, we describe the two technologies under study and the data used in our estimation. We then present the econometric specification and the estimation procedure. After discussing the results and directions for further work, we conclude with a discussion of implications for inference regarding technology adoption in strategic settings.

2 Structure and Examples

2.1 Basic game structure

We model adoption of the SPECT and PET as a static, two-stage game among hospitals. While neglecting potentially important features of the dynamic version, the static approximation of the adoption game adequately highlights the primary elements of how the competitive environment can affect profit complementarity.

A market consists of n firms that may adopt neither, one, or both of two technologies. Much of the intuition presented here extends to cases of three or more technologies; however, the analysis becomes far more cumbersome. The set of firms in the market, and hence the set of potential adopters of both technologies, is exogenous to the model. This restriction is sensible for our context because SPECT and PET services are relatively small components of a hospital's overall operations, and hence adoption of these technologies should have a negligible effect on the entry or exit decisions of hospitals as a whole. In the first stage of the game, each of the n firms chooses whether to adopt each of the two technologies. The choice set of each firm consists of the four possible combinations of adoption/non-adoption of the individual technologies, denoted $A \equiv \{(0,0),(0,1),(1,0),(1,1)\}$. The adoption decisions of all firms are made simultaneously.

After the adoption decisions are made in the first stage, all firms observe these decisions. Those that have adopted at least one of the technologies then compete in the market for diagnostic imaging services. The outcome of this second-stage oligopoly game determines the final payoffs to the firms. The precise nature of the interaction within each service submarket and between the two submarkets is left unspecified for most purposes; however, we will consider specific examples of the second-stage subgames below. We do impose the following assumption throughout:

Assumption 1. *There exists a unique equilibrium in all of the second-stage subgames. The equilibrium resulting from each market structure generated by the first-stage decisions is known to the firms in the first stage.*

Assumption 1 permits the specification of the firms' payoffs to adoption decisions directly as a function of the outcome of the first stage, without regard to the details of the subsequent play. The payoff function faced by firm i is denoted $\pi^i\colon A \times A^{n-1} \to \mathbb{R}$. The payoff to adopting neither technology, regardless of the decisions of the other firms, is fixed at zero. One should then interpret the payoffs of the other options as differences from the non-adoption option. This normalization imposes a substantive restriction given the dynamic nature of the true adoption game. In the dynamic game, the payoff to non-adoption is the value of waiting, which may differ across firms and, more importantly, across rival strategies. Nevertheless, since the normalization is required for identification of the econometric model, we impose it here as well for simplicity.

We measure profit complementarity by how much better or worse the firm would do by adopting both technologies than would two identically situated firms each specializing by adopting one technology. We denote the profit complementarity by $\Gamma^i(a^{-i})$ and define it as:

$$\Gamma^i(a^{-i}) = \pi^i\big((1,1), a^{-i}\big) - \pi^i\big((1,0), a^{-i}\big) - \pi^i\big((0,1), a^{-i}\big) \qquad (1)$$

One should not infer from the use of the term *complementarity* any restriction that Γ^i be positive. The case of negative profit complementarity is certainly plausible in many contexts, especially if the two service types are substitutes to consumers.

The changes in the complementarity of the adoption decisions across different opponent decision profiles is our particular interest. That is, if $a^{-i,1}$ and $a^{-i,2}$ are two opponent adoption profiles such that $a^{-i,2} > a^{-i,1}$, then we investigate conditions under which we can predict the sign of $\Gamma^i(a^{-i,2}) - \Gamma^i(a^{-i,1})$.[2] In particular, what conditions should be present for which we can claim that firm i's adoption decisions exhibit stronger (more positive) complementarity when an opponent has adopted a technology versus when that opponent has not?

One may see a connection between the basic game structure presented here and the theory of supermodular games developed by Topkis (1979), Vives (1990), and Milgrom and Roberts (1990b). However, only under special circumstances is the game supermodular or submodular. If we select the standard component-wise ordering as the strategy set's partial order, then a firm's profit function is supermodular if and only if $\Gamma^i(a^{-i}) > 0$ for all a^{-i}.[3] We should reiterate, however, that we do not assume that Γ^i is always positive. Furthermore, even if this were the case, the profit functions need not satisfy the increasing differences property also required for supermodularity of the adoption game. The results for supermodular games may apply to special cases, and may apply to the second-stage subgames; however, the first-stage adoption games are not in general supermodular.

Because of the agnostic view of behavior in the second-stage subgames, the structure imposed can encompass a large class of oligopoly models. The cost, of course, is that we can determine in general neither the sign of the complementarity at a particular rival decision profile, nor how the complementarity changes over rival decision profiles. We consider examples below that illustrate how assumptions regarding the second-stage play can permit predictions regarding both the level and change in profit complementarity. We reiterate that we do not impose the restrictions described below in the empirical investigation; rather, we use the intuition that these examples provide to generate predictions and interpret the results.

[2] The notation $a > b$ for vectors a and b denotes the condition that all entries of a are no less than the corresponding entries of b and that at least one entry of a is strictly greater.

[3] Given the size and structure of the choice set, the condition that Γ^i is positive is a necessary and sufficient condition for the defining inequality of the supermodularity property to be satisfied for all $a^i \in A$ at a fixed a^{-i}. All other combinations of $a^i, a^{i'} \in A$ would satisfy the inequality trivially.

2.2 Sources of Profit Complementarity

We can decompose profit complementarity in a manner that highlights its contributing sources. Specifically, we isolate the effects of self-cannibalization of revenues and cost interactions that together constitute profit complementarity. At any rival decision profile a^{-i}, the profit complementarity faced by firm i can be expressed:

$$\Gamma^i(a^{-i}) = \Delta R_1^i(a^{-i}) + \Delta R_2^i(a^{-i}) + SC^i(a^{-i}) + F_0^i \tag{2}$$

Appendix A holds the derivation of the decomposition. If the two services enabled by the technologies are substitutes to consumers, then the term $\Delta R_1^i(a^{-i})$ captures the degree to which the firm cannibalizes its net revenues from adopting the first technology by adopting the second as well. If the two services are complements, then this term instead reflects the additional net revenues from the first technology that the firm enjoys by also adopting the second. The term $\Delta R_2^i(a^{-i})$ accounts for the analogous effect on the firm's revenues from the second technology from its adoption of the first. Any variable economies or diseconomies of scope present in the joint production of the two technological services are given by $SC^i(a^{-i})$. Lastly, F_0^i represents a shared component of adoption costs that the firm occurs only once when adopting one or both of the two technologies. Note that we assume that rival adoption does not affect this shared adoption cost.

Consider the case where consumers view the two technological services as substitutes and assume that there are no variable economies of scope so that $SC^i(a^{-i}) = 0$ for all a^{-i}. If a firm faces no rival adopters of either technology, then ΔR_1^i and ΔR_2^i are both nonpositive. To see this, note that when the monopolist adopts only the first technology, it then chooses quantity (or price) to maximize its net revenues in the first service market, given that it has already incurred the relevant adoption costs. Since no quantity of the second service is produced and since no other firm produces any of the first service, the firm faces its most favorable demand curve for the first service under this situation. The maximum net revenues from the first service can therefore not be less than if the firm also produced some of the second service. By adopting the second technology and providing the associated service, the monopolist cannibalizes its net revenues in the first service market. The situation is analogous for the second service market. Hence, if a monopolist does enjoy positive profit complementarity, this complementarity stems from a large shared component of adoption costs.

Now consider the effect of rival adoption of one of the technologies in the above situation. Since we have assumed that the shared component of adoption costs does not depend on rival behavior, how rival adoption affects the profit complementarity depends wholly on how it affects the degree to which the firm cannibalizes its own technology-specific net revenues by offering both services. The first example below illustrates that if equilibrium price-cost margins are relatively insensitive to adoption, then the dominant effect of rival adoption is that the cross-firm cannibalization of revenues reduces the potential within-firm cannibalization of revenues and hence profit complementarity increases. This is not to say that the firm benefits overall from rival adoption. While the firm's technology-specific net revenues are reduced, the complementarity between its service operations increases. On the other hand, if price competition among rivals is very intense, then rival adoption can compound the ability of the firm to cannibalize its net revenues through joint adoption.

Allowing for scope economies or diseconomies in variable costs complicates the determination of profit complementarity and its changes considerably. Hence, the examples below neglect this source of the profit complementarity. Nevertheless, one should note that these economies or diseconomies of scope can be an important source of profit complementarity in some contexts. In fact, as Bulow *et al.* (1985) demonstrates, cost interactions may generate profit complementarity or anti-complementarity even where demands for the service types are independent.

2.3 Examples

We present two polar examples that illustrate how the rules of the game will affect whether profit complementarity is increasing or decreasing as rival firms adopt more technologies. The examples are chosen for their relative ease in deriving the equilibrium of each post-adoption subgame and the clarity with which they highlight the sources of change in complementarity. The first example removes any post-adoption strategy by firms to show how the effect of cross-firm revenue cannibalization on potential within-firm cannibalization will lead to increasing profit complementarity. The second example, on the other hand, demonstrates that very sensitive prices (as in the Bertrand model) will result in decreasing profit complementarity.

We also provide a variation on the first example suited to our empirical context. This third example extends the first by considering an additional source of adoption profits from feeding diagnostic imaging patients into a hospital's treatment services.

2.3.1 Example with exogenous price-cost margins

We start with a particularly tractable, albeit restrictive, example to illustrate one of the primary sources of change in profit complementarity over market structure. The key feature of the example is that service price-cost margins do not vary over the first-stage decisions of any firm. By fixing these margins, we are able to highlight the roles that within-firm cannibalization and cross-firm cannibalization play in the determination of profit complementarity. We also assume constant marginal costs and disregard cost interactions in order to focus on the cannibalization effects; however, we consider including shared adoption costs below. The basic result is that cross-firm cannibalization reduces potential within-firm cannibalization, and hence adoption by rivals will increase the profit complementarity that a firm faces in its own adoption decisions.

In this environment, there are no strategic considerations in the post-adoption subgames. So long as a firm's price exceeds marginal cost, the firm will produce to meet demand at that price if it has adopted the relevant service technology. Consumers in the market may purchase at most one unit of either type of service. The fixed-prices restriction assures that a consumer's preference ordering over the four firm-service pairs does not depend on the adoption decisions of the firms in the first stage. These adoption decisions only determine the budget set from which consumers may choose. We assume that consumers have heterogeneous preferences over the firm-service pairs and show that with sufficient heterogeneity, the profit complementarity faced by a firm will increase with rival adoption.

We find some justification for these assumptions from our empirical context. In a market with very high Medicare penetration, the assumption here of a fixed price-cost margin may be a reasonable approximation. Furthermore, if a hospital is part of a larger hospital system that interacts with HMOs on a national or regional level, the exogeneity of prices to the local market structure again seems sensible. Lastly, if hospitals provide these types of diagnostic services merely to feed patients into profitable treatment services, we may interpret the margin instead as an expected profit term per patient scan, dependent on factors exogenous to the SPECT/PET market structure.

One can find the details of the result in Appendix A. Under the stated assumptions, the adoption decisions of a firm will exhibit negative profit complementarity for any fixed adoption decisions of the other firms. The negative profit complementarity stems from the fact that the hospital will cannibalize utilization of one service by offering the other as well. That is, $\Delta R_1^i(a^{-i})$ and $\Delta R_2^i(a^{-i})$ are both negative. However, if a rival adopts an additional technology, then the complementarity faced by the firm is greater than if the rival chose not to adopt that technology. This latter result arises because the rival's adoption, in cannibalizing usage of the incumbent's services, can only reduce the incumbent's potential self-cannibalization. Again, the effect of cross-firm cannibalization on potential within-firm, cross-service cannibalization drives the result. The rival adopter takes customers from the pool that would otherwise purchase either service offered by the original firm. While this makes the original firm worse off, it reduces the ability of the firm to harm itself further by offering both services.

While adoption by a rival increases the profit complementarity between the two adoption decisions, the profit complementarity remains negative in this example without shared adoption costs. In the presence of adoption costs that are common to the two technologies, the complementarity for a fixed opponent decision profile may be driven positive; however, the change in complementarity will be unaffected. A large enough adoption cost shared between the two technologies could outweigh the self-cannibalization of quantity demanded brought about by adoption of an additional technology. However, the independence of this adoption cost to the decision of rivals ensures that it has no effect on the change in complementarity across rivals' decisions.[4]

2.3.2 Example with Bertrand competition

One should suspect that the increase in profit complementarity from rival adoption in the previous example depends substantially on the lack of pricing strategy. A monopolist has no ability to adjust prices when offering both services so as to reduce the self-cannibalization effect through price discrimination. Furthermore, adoption of a rival of the same technology does not induce competition that drives down the service price-cost margins and exacerbates the cross-firm cannibalization of revenues. We turn now to another polar case to illustrate how intense price competition among adopters may lead to decreasing profit complementarity. We shall see that Bertrand competition in the individual services, and substitution between the services, will lead to decreasing profit complementarity from rival adoption.

The source of the decreasing profit complementarity in this example is very similar to the result described in the introductory example of Judd (1985). If one firm adopts both technologies and the other adopts one of them, the price war in the service provided by both firms will not only destroy the profitability of offering that service, but the low prices will also draw consumers away from the other service, hence doubly hurting the profits of the firm that provides both. In Judd's example, the incumbent firm would even be willing to incur a positive exit cost to get out of the submarket in which the other firm entered. This willingness to pay is a fairly good indicator that the rival's strategy has negatively affected the profit complementarity between the two decisions.

In Appendix A, we provide the details of this example with Bertrand competition within service markets and Hotelling competition across service markets to illustrate that rival

[4]One can certainly imagine situations where adoption costs do change as the markets see higher numbers of competing adopters, in which case this latter result may change. For instance, if a hospital needs regulatory approval to purchase the scanners or provide these services, it may incur additional lobbying costs to persuade regulators that its adoption is not redundant.

adoption in the presence of intense price competition drives down complementarity between a firm's adoption decisions. Prices for any service that both firms provide will be driven down to marginal cost, as in the Bertrand model. Note that this result holds even if one of the firms also provides the other service because that firm can undercut the price of the other without significantly affecting the relative prices of the two services. A monopolist having adopted both technologies will be able to reduce the self-cannibalization in the services through price discrimination, although there will still be some cannibalization with travel costs in the assumed range. The resulting price war from adoption of one technology by the other firm destroys the ability of the firm that operates in both to price discriminate. Furthermore, the low prices that result from the price war draw away consumers from the neighborhood of the other service. We have then that the presence of a rival exacerbates the ability of a firm to cannibalize its revenues from adopting one technology by adopting the other.

2.3.3 Example with patient feeding

Since the investigation focuses on medical diagnostic imaging technology, one should consider that a hospital may be motivated to adopt these technologies primarily by the prospect of feeding patients into its treatment services. Under such a motivation, a hospital may care far less about the direct profits from providing the diagnostic services. The analysis of this scenario closely resembles that with exogenous price-cost margins. However, the present case predicts that profit complementarity is affected by the number of hospitals in the market, not only on their adoption decisions. While rival adoption of additional technologies increases profit complementarity just as before, profit complementarity also increases with the number of hospitals in the market.

Appendix A presents a stylized example of patient feeding to illustrate that profit complementarity is increasing not only in rival adoption, but also in the number of hospitals in the market. The example differs from Example 2.3.1 in that the increase in profit complementarity stems not only from reduced self-cannibalization in quantity, but also from a reduction in the value of each patient in the cannibalized quantity. Since patients in markets with more hospitals have more options for treatment services, the expected value to a hospital of each scanned patient decreases as the number of hospitals increases. While again this hurts the profitability of the individual technologies, it serves to increase the profits to joint adoption relative to specialized adoption by reducing the self-cannibalization of technology-specific revenues.

2.4 Testing for Changes in Profit Complementarity

The level of profit complementarity significantly affects the equilibria that tend to arise in a multi-product oligopoly game, as illustrated by Shaked and Sutton (1990). In contexts with positive complementarity, equilibria where fewer firms adopt both technologies will be more common. With negative complementarity, one would expect equilibria where a larger number of firms adopt only one of the technologies.

One may then use observations of the equilibrium patterns across markets to infer whether profit complementarity is positive or negative, subject to the limitations discussed in Section 4. If one observes that firms tend to adopt either both technologies or neither of them, then we may infer positive profit complementarity. Alternatively, if one sees a tendency of firms to adopt either one technology or the other, then we may infer negative complementarity. The accuracy of these inferences, of course, depends crucially on one's ability to control for other forces at work, especially correlation in the profitability of the individual adoption decisions.

Similarly, one may observe changes in equilibrium patterns across market structures to infer changes in profit complementarity. If profit complementarity increases with rival adoption, then we should see a stronger tendency toward firms adopting one technology or the other in less competitive markets and toward firms adopting both technologies or neither in more competitive markets. From the examples above, we suspect that contexts for which price competition is limited in intensity would tend to exhibit increasing profit complementarity.

One could, of course, impose structural assumptions on the second-stage subgames that generate increasing or decreasing profit complementarity and use this structure to reduce the degrees of freedom in testing other hypotheses regarding the model. Alternatively, one could take a "black box" approach to the second-stage subgames and use the estimated changes in profit complementarity to make inferences regarding the nature of competition within and across the submarkets.

The latter approach appears preferable for the case of hospital diagnostic imaging services. Competition among hospitals is thought to depart somewhat from conventional models of imperfect competition. The presence and strength of both insurance and intermediaries between the providers and consumers of hospital services, and the fact that most hospitals are non-profit organizations, have led market observers to question whether traditional models of competitive behavior among firms should be applied to hospitals. Papers such as Noether (1988) and Gaynor and Vogt (2003) find ambiguity in whether hospitals compete in price, quantity, or quality. Luft *et al.* (1986) find that the effect of rivalry on provision of specialized clinical services depends significantly on whether the services are intended to directly attract patients, such as twenty-four hour emergency care, or are intended to attract physician affiliations and feed patients into further treatment services, as would likely be the case for diagnostic imaging. A hospital may even have a greater incentive to provide a service also provided by a rival, independent of complementarity with other decisions, if the Medical Arms Race hypothesis holds.

We turn now to the estimation of adoption decisions regarding SPECT and PET scanners. Before considering the econometric specification, we examine the two technologies, the dataset, and assumptions on the data used in the estimation.

3 Empirical Context

3.1 SPECT and PET

The two diagnostic imaging technologies present an appropriate setting for the study of profit complementarity in multi-product oligopolies. For many diagnostic purposes, either technology may be used; however, the optimal technology varies across diagnostic procedures, especially considering their relative operating costs. In general, PET scans provide the radiologist with substantially better resolution, whereas SPECT scans cover larger areas of the body, utilize a wider variety of radiopharmaceuticals, and have a clear cost advantage.

Both SPECT and PET fall within the category of nuclear medicine imaging, or radionuclide imaging. Whereas CT and MRI scanners provide only a structural view of the inner anatomy, nuclear medicine imaging provides functional and physiological information. Rather than emitting radiation beams through the patient, as conventional X-rays, mammographs, and CT scanners do, nuclear imaging involves the injection of radiopharmaceuticals ("tracers"), which emit gamma rays as the small amounts of radioactive material decays in the body. The scanner detects these gamma rays emanating from the patient to reconstruct a two- or three-dimensional image of the organs under study.[5] For example, since cancer cells divide rapidly, they exhibit high rates of metabolic activity. They therefore absorb more of the radionuclide material than typical cells and hence show up in nuclear images as "hotspots" or "coldspots." This information enables detection of cancerous areas sooner than does either CT or MRI scanning, which look for tumors that have formed in the tissue. Furthermore, these scans can, in some instances, substitute for invasive diagnostic surgery, such as biopsy. However, radionuclide imaging has not yet reached the resolution possible with CT and MRI scans, and hence they are not widely used in areas such as mammography and are often preceded by a CT or MRI scan.

Scanning technologies involving radioisotopes actually predate even CT scanning. However, the advent of CT and MRI rendered obsolete the need to inject patients with radioactive materials. Recently, however, as technology has made the process safer and more useful, nuclear imaging has found an important place in early diagnosis of cancer, epilepsy, cardiac disease, and other particular maladies.

SPECT is the cheaper and more widely available of the two technologies. The SPECT scanners form the organ image using a gamma camera that detects the gamma rays emitted from the decay of the radioisotope that has been injected into the patient. While the principals of SPECT imaging were developed in the 1960s and prototypes had been developed by the late 1970s, the SPECT scanner did not become a clinically available technology until the late 1980s.

PET scanners detect gamma rays from two emission sources. They therefore tend to have better resolution and give more precise functional information than SPECT scanners. However, whereas PET scans primarily employ the fluorine-18 deoxyglucose (FDG) tracer, SPECT scans can use a variety of tracers, which allows improvements in the sensitivity of the scan by adapting the tracer to the targeted organ. The first PET scanner was introduced in 1977 and had made only limited diffusion into hospitals as of 1998, the year of our data. Because PET scans involve the use of a tracer with a very high rate of decay, PET scanners must be located very near a cyclotron that generates these radioisotopes. This contributes to the very substantial costs of providing PET service.

Both scanners are manufactured by essentially the same set of firms, dominated by GE and Siemens. Given the oligopoly structure of the scanner market, one may question whether adoption costs are invariant to the hospital market structure as we have assumed. Since the suppliers of these machines enjoy substantial market power, they may employ price discrimination based on the market environment in which the purchasing hospital operates. If we assume, intuitively, that the suppliers wish to sell as many types of machines to as many hospitals as it can, then the suppliers would likely partially compensate for any profit complementarity between the adoption decisions. That is, a supplier may be aware that a hospital facing no rivals in either technology faces stronger self-cannibalization in joint adoption. The supplier may then offer the dual-technology bundle to such a hospital at a substantial discount over that for a hospital facing rivals with one or more of the technologies. The data provides no means of controlling for this effect because we do not observe the make or price of the scanner purchased by the hospital. If this effect is present, then it will diminish the changes in profit complementarity over market structures. That is, the presence of this effect, and the inability to control for it, would bias the apparent changes in profit complementarity towards zero.

[5] See Lopes and Chepel (2004) and Spencer *et al.* (1995) for a detailed description and comparison of the two imaging techniques.

The fixed costs of adopting the two technologies differ enormously. While SPECT facilities can be constructed for under one million dollars, PET facilities, especially given that an on-premises cyclotron is often required to generate the tracer, are far more expensive. Keppler and Conti (2001) estimate the costs of building a PET facility as ranging from \$1.4 to \$6.2 million, depending on the quality of the scanner and whether a cyclotron is installed. Furthermore, the average variable costs of PET scans typically exceed those of SPECT scans, although the costs of both vary substantially over diagnostic procedures. One should note that Berger *et al.* (2003) finds little difference in the average cost of PET scans between those for which the FDG tracer was manufactured on premises for those for which the FDG tracer was purchased from a local manufacturer.

Given the substantial fixed costs of providing each service, one would speculate that substantial economies of scale are present in the provision of each if typical utilization is below capacity. Indeed, both Berger *et al.* (2003) and Keppler and Conti (2001) argue that per-scan PET costs decrease strongly with quantity. While SPECT scans would also exhibit strong economies of scale at lower production levels, the utilization rates of this technology tend to be higher, even reaching capacity at some institutions.

The substantial fixed costs shared between adoption of the two technologies is as an important feature of this context. The adoption of either technology generally requires the development of a nuclear medicine division of the hospital's radiology department; however, this cost would occur only once when adopting both technologies. Furthermore, radiologists and technicians trained in the one of the technologies are most likely trained in the other as well, reducing the incremental cost of recruiting personnel. These shared fixed costs contribute to economies of scope in the joint provision of the two services. On the other hand, that the two services share labor input of radiologists and technicians implies likely diseconomies of scope in variable costs that counter the economies of scope from fixed costs.

An economist may be tempted to view the two technologies as vertical substitutes. PET technology, given its better resolution and far higher cost, would be seen as the high quality scanner, whereas SPECT technology would be seen as the low quality, cost-saving technology. While not a bad approximation when analysis is restricted to specific diagnostic areas, one should be cautious about imposing this view in general. Several studies, including Bairey Merz and Berman (1997) and Spencer *et al.* (1995), have identified cases for which SPECT is the superior diagnostic technology. The Spencer *et al.* (1995) study demonstrates even quality variation within diagnoses of similar types of pathoses (e.g. types of epilepsy). For the most part, the analysis and estimation of hospital adoption decisions takes an agnostic view regarding the precise substitution patterns present on the demand-side. We do assume that consumers view the services as substitutes; however, both vertical and horizontal differentiation should generate the sort of profit complementarity patterns that we investigate.

In particular, one should note the prevalence of SPECT use in cardiological diagnostics during the late 1990s. Bairey Merz and Berman (1997) conclude that the gain in resolution from PET over SPECT does not justify the difference in cost. Furthermore, Medicare reimbursement for PET diagnostics was more or less limited to oncology. The very few cardiological PET diagnostic procedures eligible for reimbursement, such as mycardial viability, were eligible only when a previous SPECT scan was inconclusive. We will exploit the dominance of SPECT in cardiology to aid in identification through exclusion restrictions for cardiology services on PET profitability.

3.2 Data

Hospital markets are defined using the 802 Health Service Area (HSA) divisions delineated by Makuc, *et al.* (1991). This partition of U.S. counties has been utilized in other studies on medical technology, including Baker (2001), Dafny (2003), and Schmidt-Dengler (2005). Because HSA's were designed to approximate markets for hospital-based health care services, they form a more appropriate definition than the more general-purpose divisions such as the Metropolitan Statistical Areas used in Noether (1988). However, one should note that HSA's were constructed from data on Medicare patient flow between counties for routine medical services. As SPECT and PET service are beyond routine care, this market definition is likely too narrow. One would expect that a patient would be willing to travel a farther distance for a technologically intensive service like diagnostic imaging than for routine health services. Hence, the definition used presumably understates the true extent of the market for these services. Alternative approaches include markets based on a fixed radius, as in Robinson and Luft (1985) and Luft *et al.* (1986), or markets that account for flow from neighboring markets, as in Dranove, Shanley, and Simon (1992).[6] Certainly, no definition perfectly captures the true reach of strategic interaction among hospitals. The HSA is chosen as the definition mainly because it was designed to estimate markets for hospital services, despite the fact that the markets for SPECT and PET service are probably broader than the markets for basic services. In addition, that the HSA's are defined as groups of counties facilitates aggregation of county-level data to obtain the relevant market characteristics.

We assume that the set of hospitals in each market is exogenous to the adoption decisions. That SPECT and PET services are relatively small components of a hospital's overall operations justifies this assumption. We then have in each market a fixed, observable set of potential adopters of the two technologies. One qualification that arises is the question of whether there exist free-standing SPECT and PET diagnostic imaging centers that may compete with hospital-based services. While the number of free-standing clinics providing SPECT and PET service has grown in recent years, they did not have a substantial enough presence in the late 1990's to pose a problem to our estimation.

County-level data was acquired from the *Area Resource File* (ARF), which combines demographic data obtained from the U.S. Census with specialized data related to health care from the American Medical Association, the Centers for Medicare and Medicaid Services, and other sources. Data from 1998 on population size, median household income, HMO penetration, and Medicare penetration were aggregated up to the HSA level to form the market characteristics.

Hospital characteristics, including whether or not SPECT and PET are offered, are drawn from the 1999 *AHA Guide*, which was compiled from the 1998 American Hospital Association (AHA) Annual Survey. The guide provides a directory listing of almost all hospitals in the United States in 1998. The relevant information for this study include the hospital's county, control type, service type, system membership, exogenous characteristics of the hospital such as bed size and outpatient visits, and list of facilities. To be included in the sample, the institution must be a non-federal general medical and surgical hospital located in the forty-eight continental states.[7] In addition, hospitals with missing information were not included. Of the over six thousand entries in the directory, only 3135 were admissible based on this criteria.

[6]See Dranove, Shanley, and Simon (1992) for a discussion of how market definition in studies of hospital competition may bias estimation.

[7]Hospitals in Alaska, Hawaii, and the U.S. territories were not assigned Health Service Area (HSA) codes.

The *AHA Guide* (1999) provides listings for three types of associations among hospitals that may indicate joint decision: systems, networks, and alliances. A *system* is defined by the *Guide* as "two or more hospitals that are owned, leased, sponsored, or contract managed by a central organization." A *network* is defined as "a group of hospitals, physicians, other providers, insurers, and/or community agencies that work together to coordinate and deliver a broad spectrum of services to their community." Finally, an *alliance* is defined as "a formal organization, usually owned by shareholders/members, that works on behalf of its individual members in the provision of services and products and in the promotion of activities and ventures." While all three associations indicate a certain degree of coordination that may affect provision of diagnostic services, we assume that adoption decisions are coordinated at the the hospital system level. One should note that there appears to be strong correlation in the composition of the three associations, with many networks and alliances consisting only or principally of hospitals within the same system. While hospital networks have attracted scrutiny recently from antitrust agencies as possibly enabling some degree of price coordination, Burgess, Carey, and Young (2005), in their study of California hospital networks, find that evidence for joint pricing is strongest in networks of hospitals under the same system and find only weak evidence of price coordination in networks of hospitals across systems.[8]

Given our focus on strategic interaction among hospital oligopolists, the presence of markets with a large number of competing hospitals complicates our analysis. In such markets, hospitals most likely compete with only a subset of the other hospitals; however, the data does not permit us to distinguish hospitals that are linked strategically in these markets. Furthermore, because we model strategic interaction as a simultaneous game of imperfect information regarding opponents' adoption, to assume that all hospitals compete with all others raises quite exorbitantly the dimensionality of the computation of expected opponent adoption in these large markets. Therefore, we limit our sample to those markets for which we observe no more than seven hospitals.

This restriction to small markets leaves 2011 observations in 641 markets. In the sample, there are 125 monopoly hospital markets, 172 duopolies, 155 triopolies, and decreasing numbers of hospitals in markets of four to seven rival hospitals. Note that these figures count *rival* hospitals: that is, hospitals from distinct hospital systems. For example, eight of the monopoly markets contained more than one hospital, all of which were managed by the same hospital system.[9]

With only six percent of the sample adopting PET, and only one and a half percent adopting PET without also adopting SPECT, the low variation in this component of the dependent variable is cause for concern. Nevertheless, there should be sufficient variation in the choice proportions across market structures to enable estimation, so long as we are parsimonious with the characteristics that enter PET profitability and the profit complementarity between the two services.

One should also note that the sample substantially underrepresents teaching hospitals because of our exclusion of large hospital markets. When these markets are included, teaching hospitals constitute six percent of the hospitals, whereas in the sample used for

[8]As Burgess, Carey, and Young (2005) note, hospitals already in the same system may form networks to better share information and coordinate decisions among employees.

[9]The market comprised of the Minnesota counties Cottonwood, Jackson, Murray, and Nobles contained five hospitals, all of which were run by Sioux Valley Hospitals and Health System of Sioux Falls, SD. The market comprised of the Iowa counties Cerro Gordo, Franklin, Hancock, Kossuth, Winnebago, and Worth contained four hospitals, all run by Mercy Health Services of Farmington Hills, MI. The other six monopoly markets contained two hospitals.

estimation, they constitute little more than two percent.

4 Estimation

4.1 Econometric Specification

Consider hospital i with characteristics given by the vector w_i, which for now may include characteristics that are observed or unobserved, exogenous or endogenous, and hospital-specific or market-specific. For estimation, we use an indexed version of the choice set rather than the form used in Section 2. The discrete dependent variable a_i takes values in $A \equiv \{0, 1, 2, 3\}$, representing the choices respectively to adopt neither technology, adopt only SPECT service, adopt only PET service, and adopt both technologies. The payoff to firm i from choosing $j \in A$ is:

$$\tilde{\pi}^i_j = \pi_j(w_i) + \varepsilon^i_j \tag{3}$$

Each ε^i_j is independently and identically distributed as a Type I Extreme Value random variable. Without further details, the specification follows the standard multinomial logit model (MNL). However, the Independence of Irrelevant Alternatives (IIA) property well-known to the MNL model does not fit with our interpretation of the choice set. We should expect that the unobserved heterogeneity in preferences exhibits correlation between options 1 and 3 because both entail the adoption of SPECT, and between 2 and 3 because both entail the adoption of PET. Furthermore, the nested logit model would not be appropriate either, because no *a priori* ordering of the SPECT and PET nests appears any more appropriate than the others if the decisions for the two services are made jointly. Rather, we maintain the assumption that the ε^i_j are independently distributed and account for the likely correlation in unobserved heterogeneity through our treatment of the mean payoff function.

Two features of the specification permit a richer preference structure than the standard multinomial logit. First, the mean payoff function for the option denoting the joint bundle is defined as in the model detailed in Section 2. That is, the mean payoff term π_j in (3) is specified differently for the dual-adoption option than for the others. Specifically, the mean payoff to the third option is:

$$\pi_3(w_i) = \pi_1(w_i) + \pi_2(w_i) + \Gamma(w_i) \tag{4}$$

where the $\Gamma(w_i)$ term captures the complementarity between SPECT and PET adoption. The treatment here of the third option takes into account its economic interpretation. Furthermore, this specification is convenient given our aim to estimate the effects of hospital market structure on the complementarity between the decisions. This approach was proposed by Gentzkow (2005) in his study of complementarity in consumer decisions regarding print and on-line newspapers. The approach has also been used in Augereau, Greenstein, and Rysman (2005) in their study of 56K modem standards.

The mean payoff of providing neither service is normalized to zero, as is necessary given that only the payoff differences determine the observation's choice. It remains then to define the mean payoffs for the individual service options and for the complementarity term. We account for the likely correlation patterns through the specification of these mean payoff terms in a manner similar to that used in Gentzkow (2005). That is, among the hospital's characteristics are a pair of unobserved characteristics (ν^i_1, ν^i_2) that capture the heterogeneity among hospital preferences for adopting SPECT and PET individually. In particular, ν^i_1 does not enter the mean payoff for option 2 and ν^i_2 does not enter that for option 1. We assume that these characteristics are independently distributed across hospitals; however, the two characteristics for the same hospital need not be independent of each other.

Combined with our treatment of the mean payoff of the dual-adoption option, the terms (ν_1^i, ν_2^i) will allow for correlation in unobserved heterogeneity among the options. To see this, consider an expression of payoffs where these terms have been removed from w_i and π_j:

$$\begin{aligned}
\tilde{\pi}_1^i &= \pi_1(w_i) + \nu_1^i + \varepsilon_1^i \\
\tilde{\pi}_2^i &= \pi_2(w_i) + \nu_2^i + \varepsilon_2^i \\
\tilde{\pi}_3^i &= \pi_1(w_i) + \pi_2(w_i) + \Gamma(w_i) + \nu_1^i + \nu_2^i + \varepsilon_3^i
\end{aligned}$$

Even though ε_1^i and ε_3^i are independent, the unobserved preference for SPECT $(\nu_1^i + \varepsilon_1^i)$ will correlate with that of both SPECT and PET $(\nu_1^i + \nu_2^i + \varepsilon_3^i)$, and likewise for those of PET and both SPECT and PET. Correlation in unobserved preferences for SPECT and PET would be captured by correlation between ν_1^i and ν_2^i.

We assume that ν_1^i and ν_2^i follow a bivariate normal distribution with zero means, variances σ_1^2 and σ_2^2, and correlation parameter ρ. A positive value of ρ would indicate that hospitals that tend to be more profitable in adopting SPECT also tend to be more profitable in adopting PET, even if no profit complementarity exists between the two. Such positive correlation would also capture unobserved heterogeneity among hospitals in the preference for technology overall. Negative correlation, on the other hand, may imply unobserved gains from specialization in one of the imaging services. The correlation actually presents an identification problem in that correlation between ν_1^i and ν_2^i has a similar effect on the payoffs as the complementarity term Γ. This issue will be discussed further in the subsection on identification below. The other random terms, the ε_j^i's, capture the remaining idiosyncratic preferences over the alternatives.

To capture the strategic nature of the decisions, let r_1^i and r_2^i denote the number of rival hospitals in hospital i's market that adopt SPECT and PET respectively. Note that these variables count neither hospital i nor any hospital in the same system as i. The question of endogeneity with respect to the variables r_1^i and r_2^i immediately arises. In hospital markets with favorable unobserved conditions for SPECT, we would expect to see higher numbers of firms operating in this submarket. These same conditions would make hospital i more likely to adopt SPECT. Since these conditions are unobserved, the problem becomes one of omitted variable bias that induces correlation between r_1^i and ε_1^i or ν_1^i. The same problem of course arises between r_2^i and ε_2^i or ν_2^i.

To address this issue, we take the approach of Seim (2004) and model the strategic interaction among rival hospitals as a simultaneous discrete game of imperfect information. Instead of observing the number of rival adopters, hospital i forms beliefs regarding the choice probabilities, P_{-i}, of its rivals and uses these beliefs to construct expectations of how many rivals it would face in each service. With these beliefs and the hospital's observable exogenous characteristics x_i, the expected profitability of the individual adoptions are specified:

$$\begin{aligned}
\pi_1(x_i, P_{-i}, \nu^i) &= \alpha_1 + x_i'\beta_1 + \delta_{11}E\big[\ln(1+r_1^i)\big|P_{-i}\big] + \delta_{12}E\big[\ln(1+r_2^i)\big|P_{-i}\big] + \nu_1^i \\
\pi_2(x_i, P_{-i}, \nu^i) &= \alpha_2 + x_i'\beta_2 + \delta_{21}E\big[\ln(1+r_1^i)\big|P_{-i}\big] + \delta_{22}E\big[\ln(1+r_2^i)\big|P_{-i}\big] + \nu_2^i \qquad (5)
\end{aligned}$$

The use of the logarithm in (5) gives the payoffs the desirable property that the marginal effect on profits of additional rival adoption decreases with the number of rivals. That is, the adoption by a third firm would have less of an effect on profits than the adoption by a second firm, and so on. This functional assumption was proposed by Berry (1992) and has become fairly standard in discrete choice entry models.

The complementarity term is similarly specified:

$$\Gamma^i(P_{-i}) = \alpha_3 + x_i'\beta_3 + \delta_{31}E\big[\ln(1{+}r_1^i)\big|P_{-i}\big] + \delta_{32}E\big[\ln(1{+}r_2^i)\big|P_{-i}\big] \tag{6}$$

In the actual estimation, we exclude from the complementarity term the exogenous characteristics x_i, with the exception of the number of rival hospitals present in the hospital market. These restrictions are not innocuous, as it is conceivable that many of the same characteristics that effect the profitability of providing SPECT or PET service also effect the degree to which the two services interact. Nevertheless, given that our focus is on the effects of the strategic variables, these exclusions are reasonable in the interest of parsimony.

One might ask why Equations (5) and (6) do not include a term dependent on the number of rivals in *both* submarkets. Such a term is excluded mainly for simplicity. The specifications of the profitability of the individual services and the complementarity between them represent an environment where a hospital loses some business to each rival in each submarket, but is unaffected by the identities of these rivals and their other enterprises. A richer model of the underlying competition may take into account a hospital's incentives to signal quality through the provision of multiple services and even some coordination among rival firms that operate together in both submarkets. In such cases, the inclusion of a term for the number of hospitals that operate in both markets may be appealing, even if the identities of the rivals are still brushed aside. In the present context, however, we envision that a hospital does not care that a rival is present in both markets, only that the rival is stealing business in each of the submarkets.

Equations (5) and (6) complete the specification of the option payoff functions:

$$\begin{aligned}
\pi_0(x_i, P_{-i}, \nu^i) &= 0 \\
\pi_1(x_i, P_{-i}, \nu^i) &= \alpha_1 + x_i'\beta_1 + \delta_{11}E\big[\ln(1{+}r_1^i)\big|P_{-i}\big] + \delta_{12}E\big[\ln(1{+}r_2^i)\big|P_{-i}\big] + \nu_1^i \\
\pi_2(x_i, P_{-i}, \nu^i) &= \alpha_2 + x_i'\beta_2 + \delta_{21}E\big[\ln(1{+}r_1^i)\big|P_{-i}\big] + \delta_{22}E\big[\ln(1{+}r_2^i)\big|P_{-i}\big] + \nu_2^i \\
\pi_3(x_i, P_{-i}, \nu^i) &= \pi_1(x_i, P_{-i}, \nu^i) + \pi_2(x_i, P_{-i}, \nu^i) + \Gamma(P_{-i})
\end{aligned} \tag{7}$$

A hospital's beliefs about its rivals' choice probabilities will be determined by what information about the rival the hospital observes. The following assumption characterizes the information available to hospitals.

Assumption 2. *All exogenous market characteristics and hospital characteristics of each hospital in the market (i.e. all x_i) are observable to every hospital in the market. The terms ν_1^i, ν_2^i, and ε_j^i for $j \in A$ are privately known to hospital i.*

Assumption 2 effectively states that rivals to hospital i observe no more information about i than does the econometrician.[10] The assumption is admittedly strong. We would expect that hospitals would have better information about their rivals, having interacted with them in the market repeatedly, than does an outside observer. One might desire to model this informational feature by allowing rival hospitals to observe ν_j^i, perhaps imperfectly, and allow hospital i to retain ε_j^i as private information. For our purposes, such an embellishment would come at great computational cost because we would have to integrate

[10] In fact, they observe less because they do not see a^i.

the equilibrium choice probabilities over the distribution of (ν_1^i, ν_2^i). We retain the interesting case of allowing rivals to observe some of the unobserved characteristics of the hospital as a subject for future research.

We assume that in equilibrium, the conjectured beliefs match the actual choice probabilities implied by the observed exogenous characteristics. Let $\psi(P_{-i}; x_i)$ denote the mapping that gives a hospital's best response choice probabilities conditional on its characteristics vector x_i and the choice probabilities of its rivals P_{-i}. Note that the range of ψ is the three-dimensional unit simplex. Entry j of $\psi(P_{-i}; x_i)$, denoted $\psi_j(P_{-i}; x_i)$, is the probability that option $j \in A$ is the best response of hospital i to the rival choice probabilities P_{-i}, given its own characteristics x_i. The probabilistic nature of the hospital's best response reflects the fact that the econometrician does not observe the hospital's private information, and therefore can not determine with certainty whether any option is or is not optimal. Given our assumptions regarding payoff equations and the distribution of ε_j^i, the best response mapping is:

$$\psi_j(P_{-i}; x_i) = \int_{\nu^i} \frac{\exp\big[\pi_j(x_i, P_{-i}, \nu^i)\big]}{\sum_{k=0}^{3} \exp\big[\pi_k(x_i, P_{-i}, \nu^i)\big]} \, f_\nu(\nu^i) \, d\nu^i \tag{8}$$

where f_ν is the bivariate normal probability density function with mean parameters 0 and with variance and correlation parameters given by σ_1^2, σ_2^2, and ρ.

For a market of n hospitals, let $\Psi(P) \equiv \big(\psi(P_{-i}; x_i)\big)_{i=1}^{n}$ denote the mapping that provides the best response choice probabilities for all hospitals in the market given that hospitals take their beliefs regarding rivals from P. An equilibrium is a vector of choice probabilities P that is a fixed point of the mapping Ψ: that is, $\Psi(P) = P$.

The presence of multiple equilibria stands as a fundamental problem of discrete strategic models of this type. Depending on the hospital characteristics and model parameters, there may exist several fixed points of Ψ. For instance, suppose that there are two rival hospitals A and B in the market and that the parameters and characteristics are such that the option payoffs are symmetric among the hospitals. In this case, there will exist a symmetric equilibrium; however, there may also exist other equilibria. If hospital A believes B will adopt SPECT with a high probability, and if B's adoption reduces the profitability of adopting SPECT, then A will likely adopt that technology with only low probability. Given that A will adopt with only low probability, B would likely find adoption of SPECT profitable, and hence choose to adopt with high probability. Of course, the roles could also be reversed. Furthermore, the presence of two technologies presents the opportunity for equilibria where A adopts both and B adopts neither (or vice-versa), and where A adopts one and B the other (or vice-versa). We address this issue in Section 4.2 below.

We will estimate the parameters of the model using a variation on maximum likelihood estimation. Let $\theta \equiv (\alpha', \beta', \delta', \sigma_1, \sigma_2, \rho)'$ denote the parameters to be estimated. Let the sample consist of L hospital markets, where market l consists of n_l hospitals, so that the full sample consists of $n \equiv \sum_{l=1}^{L} n_l$ observations. Let a^l denote the vector of observed choices of the hospitals in the market, let X^l denote the matrix of their characteristics, and let a and X denote the full sample counterparts to a^l and X^l. The log-likelihood function is then:

$$\ln \mathscr{L}(\theta; a, X) = \sum_{l=1}^{L} \sum_{i=1}^{n_l} \sum_{j=0}^{3} 1\{a_i^l = j\} \cdot \ln \psi_j\big(P_{-i}^l(\theta, X^l); x_i^l, \theta\big) \tag{9}$$

where

$$\psi_j(P_{-i}^l; x_i^l, \theta) = \int_{\nu^i} \frac{\exp\big[\pi_j(x_i^l, P_{-i}^l, \nu^i; \theta)\big]}{\sum_{k=0}^{3} \exp\big[\pi_k(x_i^l, P_{-i}^l, \nu^i; \theta)\big]} \, f_\nu(\nu^i; \theta) \, d\nu^i \tag{10}$$

and where $P^l(\theta, X^l) = \Psi\big(P^l(\theta, X^l); \theta, X^l\big)$.

4.2 Identification

Before discussing the estimation procedure, we must address the issue of identification of the model. For this purpose, we consider first the identification of the parameters when the true equilibrium choice probabilities are known. We then consider the additional challenges brought about the fact that we do not observe these choice probabilities.

Suppose first that we knew the true choice probabilities P^{l*} that characterize the equilibrium of each market l. If this were the case, P^{l*} would be a fixed point of the best-response mapping at the true parameter values θ^*. If θ^* is the only parameter vector such that $P^{l*} = \Psi(P^{l*}; \theta^*, X^l)$ for all l, then these parameters are identified by the fixed-point mapping. However, if there exists another parameter vector $\theta \neq \theta^*$ such that $P^{l*} = \Psi(P^{l*}; \theta, X^l)$ for all l, then the model is not identified. Indeed, the log-likelihood function in (9) would evaluate to the same values at both θ^* and θ when evaluated at the true choice probabilities. A necessary condition for identification is therefore:

Assumption 3. *There exists a unique vector of parameters for which the true choice probabilities constitute an equilibrium. That is, there exists $\theta^* \in \Theta$ such that for all $\theta \in \Theta$, $\theta \neq \theta^*$, there exists $l \in \{1, \ldots, L\}$ such that $P^{l*} \neq \Psi(P^{l*}; \theta, X^l)$.*

One issue, as mentioned above, concerns the constant in the complementarity term (α_3) and the correlation parameter (ρ) between the unobserved profitability shocks to SPECT and PET. As noted above, and discussed in Manski (1993), Athey and Stern (1998), Gentzkow (2005), and Augereau, Greenstein, and Rysman (2005), these two parameters have a very similar effect on the choice probabilities. If hospitals tend to provide both services or neither of them, then this could imply either positive complementarity or positive correlation in ν_1^i and ν_2^i. Likewise, tendency toward specialization in individual services may be generated by negative complementarity or negative correlation. While the non-linearity of the choice model may permit separate identification of α_3 and ρ, we would not want to rely on this source because it is sensitive to functional form. We observe hospital characteristics related to cardiology services that may comfortably be excluded from the profit equation of PET adoption, and these exclusions will aid in separating the effects of the complementarity and the correlation.

The complementarity constant and correlation term, however, are of less interest than the parameters δ_{31} and δ_{32}, which capture the effects of rival entry on complementarity. If the correlation in unobserved heterogeneity changes across market structure, then we have an identification problem with respect to these parameters as well. For identification of these parameters, we require the following assumption:

Assumption 4. *The correlation between ν_1^i and ν_2^i is not affected by number of rival hospitals faced by i, nor by the probabilities with which they enter the two submarkets.*

The assumption states that market structure has no effect on the unobserved heterogeneity that generates a tendency for a hospital that is more profitable in one market to be more or less profitable in the other market. If we imagine that such unobserved heterogeneity stems from some hospitals being better suited to employ medical technology because of personnel or experience, then the assumption appears reasonable. Once this assumption is imposed, the identification problem presented by the correlation in unobserved heterogeneity is contained to the identification of the constant level of complementarity between the two services.

For separate identification of the complementarity constant and the correlation parameter, we exclude the indicators for cardiology treatment services from PET profitability. With these restrictions, any apparent effect of variation in cardiology services on PET adoption will stem from complementarity between the adoption of the technologies. To see this, suppose first that there is no complementarity between the two technologies and that the presence of cardiology services increases the profitability of SPECT adoption. We should then see that hospitals that offer cardiology services would more likely adopt SPECT. However, there would be no such effect on PET adoption, regardless of whether the unobserved preferences are correlated. Now suppose that there is positive complementarity between the adoption decisions. Although the presence of cardiology services does not directly affect the profitability of PET adoption, the indirect effect through the increase in SPECT adoption and positive complementarity will serve to increase the likelihood of PET adoption.

The fact that we do not observe the true choice probabilities presents additional issues with respect to identification. In particular, as with many strategic models, the presence of multiple equilibria at some parameter values complicates the identification question. If for some X^l and θ, the mapping $\Psi(\cdot\,; \theta, X^l)$ has multiple fixed points, then the log-likelihood function in (9) is not well-defined at these values. In such cases, the different equilibria will likely generate different values for the log-likelihood function and, without an equilibrium selection mechanism, we can not distinguish the "correct" value. If there are multiple equilibria at the true parameter values θ^*, then again the log-likelihood function at the true parameters is not well defined and the model is not identified.

We therefore require that the equilibrium at the true parameters be unique. We justify this assumption by noting the exogenous asymmetry of hospitals in the markets that constitute our sample. Multiple equilibria are far more likely in markets for which the firms are nearly symmetric than for markets where substantial asymmetries exist. For example, in a market with one large hospital and one small hospital, the profits of the large hospital are likely far less sensitive to rival adoption than those of the small hospital. In the extreme, the hospitals in a simultaneous entry game behave as they would in a sequential adoption game where the large hospital moves first. In general, the more exogenous variation in the hospital characteristics among rivals in a market, the more dominating these characteristics are relative to the strategic effects in determining the best-response choice probabilities, and hence the less likely two different vectors of choice probabilities would constitute an equilibrium. To check the validity of this assumption, we check that the equilibrium is unique at the estimated parameter values.

While multiple equilibria at other parameter vectors clearly present challenges to the *search* for the parameters, the model is identified so long as the equilibrium at the true parameters is unique and Assumption 3 holds. To see this, consider the following function:

$$\Upsilon\big(P; a, X\big) = \sum_{l=1}^{L} \sum_{i=1}^{n_l} \sum_{j=0}^{3} 1\{a_i^l = j\} \cdot \ln p_{ij}^l$$

where p_{ij}^l is the choice probability of option j for hospital i in market l under the choice probabilities P. If $P \neq P^*$, then there exists a sample of observed choices a such that $\Upsilon(P; a, X) \neq \Upsilon(P^*; a, X)$.

If we allow for multiple equilibria at $\theta \neq \theta^*$, then the log-likelihood in (9) becomes a correspondence. That is, $\ln \mathscr{L}(\theta; a, X) = \big\{\Upsilon(P; a, X) : P = \Psi(P; \theta, X)\big\}$. Since P^* is the only equilibrium at θ^*, $\ln \mathscr{L}(\theta^*; a, X)$ is single-valued. For identification, we must have that for any $\theta \neq \theta^*$, there exist samples for which $\ell \neq \ln \mathscr{L}(\theta^*; a, X)$ for all $\ell \in \ln \mathscr{L}(\theta; a, X)$.

So long as $P^* \neq \Psi(P^*;\theta,X)$, then there exists a sample of observed choices such that $\Upsilon(P;a,X) \neq \Upsilon(P^*,a,X)$ for all P that are equilibria under $\theta \neq \theta^*$. By Assumption 3, P^* is an equilibrium *only* under θ^*, and hence $\ell \neq \ln \mathscr{L}(\theta^*;a,X)$ for all $\ell \in \ln \mathscr{L}(\theta;a,X)$.

One can think of the estimation problem as jointly estimating the parameters and the choice probabilities. Sufficient variation in the observed choices will prevent other choice probabilities from appearing equally likely as the true probabilities. Sufficient variation in the exogenous hospital characteristics ensures that only the true choice probabilities constitute an equilibrium under the true parameters and that only the true parameters will generate the true choice probabilities as an equilibrium.

We now consider the procedure used to estimate the parameters of the SPECT and PET adoption game. We choose an approach that is robust to the presence of multiple equilibria at intermediate parameter values and that is computationally tractable.

4.3 Nested-Pseudo Likelihood Estimation

To estimate the structural parameters, we employ the Nested Pseudo-Likelihood (NPL) algorithm described in Aguirregabiria and Mira (2004) and Aguirregabiria (2004a). The procedure involves recursively maximizing a pseudo-likelihood function with respect to the parameters, holding rival choice probabilities fixed, and then updating rival choice probabilities by finding an equilibrium under the optimal parameters. An alternative approach, such as in Seim (2004), is to find an equilibrium at every guess of the parameter vector and then evaluate the likelihood function using those choice probabilities. The NPL has two advantages over the nested fixed-point method. First, the pseudo-likelihood function, unlike the actual likelihood function, is always well-defined, even in the presence of multiple equilibria at a particular parameter vector. Secondly, the NPL reduces the number of fixed point searches considerably, resulting in substantial computational gains.

While Aguirregabiria and Mira (2004) consider the estimation of a dynamic model with discrete exogenous characteristics, we use the approach for the estimation of a static model with some continuous characteristics present. The use of the procedure for static models involving a fixed-point search is described in Aguirregabiria (2004a) and Aguirregabiria (2004b). The fact that we include continuous characteristics does not alter the properties of the estimator. The requirement of characteristics with a discrete support is needed in dynamic models because such settings require the construction of a global state transition matrix. However, we have no need of such transition matrices in static settings.

We define the pseudo-likelihood function similarly to the actual likelihood function in (9). The pseudo-likelihood function takes fixed choice probabilities as an argument, rather than having them implicitly defined as a fixed point of the equilibrium mapping under the input parameters and data, as in the actual likelihood function. The function is then:

$$\ln \mathscr{L}^P(\theta;P,a,X) = \sum_{l=1}^{L}\sum_{i=1}^{n_l}\sum_{j=0}^{3} 1\{a_i^l = j\} \cdot \ln \psi_j\left(P_{-i}^l; x_i^l, \theta\right) \qquad (11)$$

The gain from fixing the choice probabilities as an explicit argument is that the pseudo-likelihood function is always well-defined. Of course, a parameter vector that maximizes $\ln \mathscr{L}^P$ at arbitrary choice probabilities is not the maximum likelihood estimate.

How the procedure works is best illustrated by first considering a simpler two-stage estimator. The first stage involves consistently estimating the choice probabilities non-parametrically, which with continuous explanatory variables would require the use of kernel methods. Let $\hat{P}$ denote this estimator. In the second stage, we then choose $\hat{\theta}$ as:

$$\hat{\theta} = \underset{\theta \in \Theta}{\operatorname{argmax}} \ \ln \mathscr{L}^P(\theta; \hat{P}, a, X) \tag{12}$$

Aguirregabiria and Mira (2004) show that this two-stage estimator is consistent and asymptotically normal. Notice that this estimator overcomes the problem of multiple equilibria by looking to the data, including the observed choices, to select choice probabilities. Note also that it does not require an equilibrium search. The two-stage estimator, while convenient, may suffer from severe finite sample bias if the choice probabilities are poorly estimated. In contexts with many explanatory variables, like the present one, non-parametric estimators of the choice probabilities, while consistent, may be very imprecise. The precision of the resulting parameter estimates will suffer as a result.

By iterating further, we not only improve on the two-stage estimator, but we are also able to drop the requirement that the initial estimator of the choice probabilities be consistent. Starting with an initial guess of the choice probabilities $\hat{P}^0$, we maximize the pseudo-likelihood function in (12) to obtain a parameter vector $\hat{\theta}^1$. We then find an equilibrium $\hat{P}^1$ by finding a fixed point of the equilibrium mapping under $\hat{\theta}^1$. We repeat this process until further iterations do not change the guess of the equilibrium choice probabilities. Upon convergence of the algorithm, we have an estimate of the parameter vector $\hat{\theta}$ and of the equilibrium choice probabilities $\hat{P}$. We initialize the search at multiple initial guesses and if these initial guesses result in convergence to different points, we choose as the estimate the resulting parameters and choice probabilities that have the highest pseudo-likelihood value.[11]

One should note that convergence of the NPL is not guaranteed in general. That is, the search could potentially enter a cycle among several parameter vectors and choice probabilities. In most of the specifications and trials run for the present investigation, the algorithm converged. In cases where it did enter a cycle, the culprit always was lack of separate identification of the parameters due to the limitations of the sample.

If the NPL does converge, then the resulting estimator $(\hat{\theta}, \hat{P})$ is consistent and asymptotically normal. One can find the full proof of these properties in Aguirregabiria and Mira (2004) and we summarize the argument for consistency in Appendix B. The asymptotic covariance matrix, however, is a cumbersome function of the pseudo-score variances and the Jacobian of the choice probabilities. The standard errors can also be estimated via a bootstrap method, which will also provide a better idea of the finite sample variance.

To implement the NPL algorithm, we use successive approximations to find a fixed point of Ψ for each market, given the current values of the parameters. In both computing the pseudo-likelihood and updating the choice probabilities through the mapping Ψ, we use Monte Carlo integration to approximate the integral in (8). Specifically, for each observation, we draw S realizations from the bivariate normal distribution under the parameters $(\sigma_1^2, \sigma_2^2, \rho)$ and compute the approximated integral as:

$$\hat{\psi}_j^S(P_{-i}; x_i, \nu^i) = S^{-1} \sum_{s=1}^{S} \frac{\exp\left[\pi_j(x_i, P_{-i}, \nu_s^i)\right]}{\sum_{k=0}^{3} \exp\left[\pi_k(x_i, P_{-i}, \nu_s^i)\right]} \tag{13}$$

One should note that the simulated maximum likelihood approach used exhibits simulation bias in the evaluation of the log-likelihood function. While $\hat{\psi}_j^S$ is an unbiased

[11] This rule was never binding. All starting choice probabilities in each experiment resulted in convergence to the same choice probabilities and parameters.

estimator for ψ_j, the estimator $\ln \hat{\psi}_j^S$, while consistent, is biased for $\ln \psi_j$ with a finite number of replications. Note that this bias does not appear in the equilibrium search because the the equilibrium search uses the level of the choice probabilities rather than the logarithm. To reduce the simulation bias, we draw the simulated characteristics using Halton sequences as described in Train (1999). We use 500 replications in the actual estimations and note that the parameter estimates do not change substantially by increasing the number of replications beyond this level.

One can find further details regarding the implementation in Appendix B. The algorithm performed very well in most cases. The successive approximations equilibrium search rarely took more than a handful of iterations through the hospitals. The rapidity likely stems from the use of the logistic form for the choice probabilities, the wide variation in exogenous hospital characteristics, and the additional smoothing provided by the technology-specific errors. Even with rather strict convergence criteria, the outer NPL loop rarely exceeded thirty iterations.

5 Results

Given that most consumers view these scanning services as substitutes, and given that price competition among hospitals for diagnostic imaging services is likely low relative to conventional markets, we expect that profit complementarity increases as each service market becomes more competitive. The intuition again is that the additional cross-hospital cannibalization in quantity that comes from adoption by rivals decreases the potential for self-cannibalization from offering both services as opposed to only one. The additional price competition from rival adoption should not be intense enough to counter this effect. The level of complementarity for monopolist hospitals will depend on how strong the shared adoption costs are relative to the self-cannibalization effect. If the shared component of fixed adoption costs is not too high relative to the self-cannibalization effect, then we would expect profit complementarity to be negative for hospitals in monopoly markets and to grow toward zero as the hospitals face more competitors in each of the service markets. Otherwise, we would expect profit complementarity to start positive for monopolists and grow as we see more rival adoption.

Both profit equations for the individual technologies include as explanatory variables the log values of bed size and outpatient visits. These continuous variables provide a high degree of exogenous variation among hospitals in a market.[12] In addition, indicators for non-profit status and community hospital status were included in both equations, private for-profit hospitals being the reference group.

An indicator for whether the hospital offers oncology services is included in the profit equations of both technologies. Hospitals that offer cancer treatment services will likely benefit more from offering these technologies, which tend to perform well and are commonly used in cancer diagnosis. Adopting these technologies and offering cancer-related diagnostic services will feed patients into the treatment services, hence raising the profitabilities relative to hospitals that do not offer oncology services. Indicators for cardiac catheterization laboratory (CCL), angioplasty, cardiac intensive care, and open-heart surgery were included in SPECT profitability, but excluded from the profitability of PET, reflecting the

[12] One may argue that outpatient visits has an endogenous component because they are affected by the adoption decisions. However, the contribution of SPECT and PET services to the overall number of outpatient visits and to overall expenditure is sufficiently small that the exogeneity of these variables is very reasonable.

far greater usage of SPECT in cardiology. The presence of these indicators implies that a hospital is strong in cardiology. Since SPECT technology tends to perform better in cardiology diagnostics, we would expect that these hospitals would be more likely to adopt SPECT. On the other hand, the presence of these services should have no substantive direct effect on PET profitability, and are therefore excluded from PET profitability. As discussed in Section 4.2, these exclusion restrictions help to separately identify the complementarity constant from the correlation in unobserved preferences.

An indicator for teaching hospitals was included in the SPECT equation; however, it could not be included in the PET equation because of collinearity with the constant term in PET profitability (no teaching hospital in the sample adopted only PET).

Both equations include the log values of population and median household income and the levels of HMO and Medicare Part B penetration as exogenous market characteristics. These variables capture heterogeneity among hospital markets that may affect the profitability of adopting each technology. Larger and wealthier hospital markets should raise the profitability of adopting each technology by raising prospective utilization. Rival hospitals in markets with relatively high HMO penetration may engage in more intense price competition, and hence we would expect that higher HMO penetration reduces the profitability of providing SPECT or PET service. Note that while Medicare covered a variety of diagnostic procedures relating to SPECT, Medicare PET coverage had just been introduced in 1998 and was limited to a very restricted group of cancer-related diagnostic groups. A patient covered by Medicare would therefore face higher opportunity costs in getting a PET scan as opposed to a SPECT scan relative to non-Medicare patients. Higher Medicare penetration should therefore shift the demand curve for PET and make the provision of this service, and hence adoption of this technology, less profitable.

As we have discussed, patient-feeding behavior on the part of hospitals would predict that both the profitability of the individual technologies and the complementarity between them will be affected by the number of hospitals in the market. We include the log of the number of hospitals in the individual profitability equations and in the complementarity equation. Given that much of the effect of an increase in the number of hospitals on the profitability of an individual technology likely stems from the additional competition in treatment services, the effect on the two individual profitabilities should be symmetric. To improve the precision of our estimates, we impose this restriction.

For the endogenous characteristics, we include the expected number of rival adopters of the SPECT and the expected number of rival adopters of PET in both profit equations. We include the cross terms because the services are substitutes to consumers and therefore rival adoption of one technology should affect the profitability of adopting the other, independent of profit complementarity between the technologies. These expectations are also included in the profit complementarity equation. All three equations contain constant terms.

5.1 Bivariate Probit Estimation

Before presenting the results of the structural estimation, we first consider a bivariate probit estimation of the adoption decisions. This first specification does not account for any complementarity between the two technologies. If there exists profit complementarity, then this complementarity will affect the estimate of the correlation parameter of the bivariate error distribution. We look for changes in profit complementarity by running the estimation over restricted samples: that is, we run the estimation for disjoint samples consisting of markets with one through four hospital systems present. If profit complementarity increases as hospital markets become more competitive, we should see higher estimates of the correlation parameter in markets with more rival hospitals present. Under Assumption 4, the actual correlation in unobserved heterogeneity is not affected by the competitive environment. Apparent changes in correlation across market structure will stem from changing profit complementarity.

Only a subset of the variables used in the main specification could be included in the bivariate probit estimation on restricted samples. We observe only 139 observations in monopoly markets and this subsample lacks sufficient variation in several of the variables to enable estimation of the full set of parameters. For the sake of comparison, we maintain the same set of variables for all subsamples.

Table 1 holds the parameter estimates for the bivariate probit specification. Of particular interest is the estimate of the correlation parameter. For monopoly markets, the estimate is negative, though not significantly so. For the duopoly subsample, the estimated parameter is positive, but only marginally significant. However, for the subsamples of markets with three and four rivals, the correlation is very significantly positive. While the lack of precision for most of the parameter estimates for the monopoly subsample make inference problematic, the fact that the correlation between the profitability of the two technologies appears to increase provides at least preliminary evidence that complementarity between the two technologies is greater in more competitive markets.

Note that we can not separately identify the contributions of the complementarity and the correlation in unobserved preferences factor in any single subsample using this specification. However, only the complementarity should change as the market becomes more competitive. If the individual profitabilities are positively correlated, then the more strongly negative profit complementarity in monopoly markets counters this actual correlation and decreases the apparent correlation for these markets. For the subsamples with three or four rivals in each market, the self-cannibalization effect is less strong and hence the level of profit complementarity has less effect on the apparent correlation. Again, precise inference is difficult in this specification; however, the change in the estimated correlation across these subsamples fits the pattern we would expect.

Since this specification does not explicitly include the strategic variables in the specification, one may wonder whether the changes in the individual profitabilities of the technologies over market structure, rather than the profit complementarity between the technologies, could be driving the apparent change in correlation. Adoption by a rival of even just one of the technologies should decrease the profitability of adopting *both* technologies because the two imaging services are substitutes to consumers. Hospitals in markets with more rivals should expect more rival adoption of one or both of the technologies, and hence their expected profitability from adoption of both technologies will be lower. However, since the individual profitabilities move in the same direction, the effect of additional rivals on the individual profitabilities should not influence the estimate of the correlation between the two technologies.[13]

5.2 NPL Estimation

Table 2 presents parameter estimates for the structural specification. One should note an important qualification of the results. The reported standard errors are those based on the Hessian of the pseudo-likelihood function at the final parameter estimates. These are

[13] If the Medical Arms Race hypothesis holds, then adoption by a rival of one of the technologies may provide greater incentive to adopt that technology and the other. If this is the case, then the profitability of adoption of both will appear to increase with rival adoption. The same logic applies: the key is that the profitabilities of the individual technologies move in the same direction.

Table 1: Bivariate Probit Specification

ρ	$n = 1$	$n = 2$	$n = 3$	$n = 4$	all
	-0.037	0.307	0.600	0.468	0.345
	(0.236)	(0.155)	(0.108)	(0.137)	(0.075)

SPECT	$n = 1$	$n = 2$	$n = 3$	$n = 4$	all
Constant	-7.458	-3.690	-5.358	-6.807	-6.024
	(8.313)	(5.358)	(4.103)	(5.329)	(2.553)
Beds(log)	0.182	0.030	0.267	0.299	0.208
	(0.251)	(0.133)	(0.105)	(0.120)	(0.063)
Outpat.(log)	0.285	0.445	0.178	0.227	0.244
	(0.206)	(0.116)	(0.084)	(0.101)	(0.052)
Community	-0.218	-0.044	-0.163	-0.210	-0.164
	(0.275)	(0.170)	(0.142)	(0.165)	(0.084)
Oncology	0.754	0.474	0.649	0.307	0.506
	(0.301)	(0.184)	(0.154)	(0.179)	(0.092)
Heart Surg.	0.269	0.402	0.216	0.077	0.221
	(0.373)	(0.237)	(0.188)	(0.205)	(0.111)
Pop. (log)	0.256	0.217	-0.152	0.321	0.097
	(0.213)	(0.178)	(0.132)	(0.233)	(0.081)
HMO	-0.651	0.005	-0.734	-0.487	-0.411
	(1.530)	(0.702)	(0.679)	(0.666)	(0.368)
Medicare	5.771	-3.318	0.326	1.539	0.551
	(3.986)	(2.982)	(2.097)	(2.697)	(1.299)
Income (log)	-0.064	-0.378	0.314	-0.131	0.066
	(0.755)	(0.475)	(0.373)	(0.478)	(0.230)
PET	$n = 1$	$n = 2$	$n = 3$	$n = 4$	all
Constant	6.459	-7.197	1.204	11.949	0.943
	(11.139)	(8.066)	(6.516)	(10.684)	(4.013)
Beds(log)	0.011	0.209	-0.027	0.527	0.184
	(0.358)	(0.213)	(0.169)	(0.255)	(0.104)
Outpat.(log)	0.190	-0.083	-0.054	-0.477	-0.124
	(0.300)	(0.166)	(0.135)	(0.178)	(0.079)
Community	-0.460	0.045	0.060	-0.240	-0.099
	(0.431)	(0.288)	(0.233)	(0.314)	(0.140)
Oncology	0.263	0.435	0.470	0.529	0.404
	(0.460)	(0.356)	(0.292)	(0.392)	(0.171)
Heart Surg.	0.209	0.711	1.055	0.666	0.711
	(0.476)	(0.315)	(0.269)	(0.372)	(0.157)
Pop. (log)	-0.159	0.178	0.334	-0.065	0.036
	(0.323)	(0.275)	(0.251)	(0.433)	(0.137)
HMO	-0.573	0.641	-1.321	0.535	-0.106
	(2.023)	(0.979)	(1.117)	(1.389)	(0.591)
Medicare	-8.644	1.983	-7.968	3.248	-3.634
	(6.265)	(4.254)	(4.166)	(5.184)	(2.239)
Income (log)	-0.699	0.258	-0.507	-1.121	-0.234
	(0.996)	(0.706)	(0.594)	(0.995)	(0.362)
Obs.	139	384	521	385	1429

Notes: Standard errors are in parentheses.

not the best estimates of the standard errors for the NPL estimator. The best asymptotic approximation to the standard errors would take into account the Jacobian matrix of equilibrium mapping with respect to both the input choice probabilities and the parameters. The use of the bootstrap method for the estimation of these standard errors both appears more practical and will provide a better idea of the finite sample variance. Future development of this work will include bootstrapped standard errors.

The primary parameters of interest are the coefficients on the strategic terms, and in particular, the coefficients on the strategic terms that enter the profit complementarity equation. While these coefficients have the predicted sign, the lack of precision with which they are estimated renders them insignificant. This lack of precision in these coefficients may stem from the low proportion of the sample that adopts only PET technology. The standard errors on the estimates of the strategic coefficients that enter PET profitability ($\hat{\delta}_{21}$ and $\hat{\delta}_{22}$) and on those that enter the profit complementarity ($\hat{\delta}_{31}$ and $\hat{\delta}_{32}$) indicate that the sample does not provide sufficient variation to separate these parameters precisely. One might restrict δ_{21} and δ_{22} to zero in order to improve the precision of $\hat{\delta}_{31}$ and $\hat{\delta}_{32}$; however, we could not be sure that resulting estimates reflect the effect of rival adoption on PET profitability or on the complementarity between SPECT and PET.

Another possibility is that we may have overestimated the degree of substitutability between the two technologies for consumers. If the two scanning technologies are only weakly substitutable, then any profit complementarity between the adoption decisions stems from the shared adoption costs. Since this cost does not vary over rival adoption, we would see very little difference in profit complementarity from rival adoption.

We find that the number of hospitals in the market has a significant negative effect on the profitability of the individual technologies. Furthermore, the number of hospitals has a significant positive effect on the profit complementarity between the adoption decisions. These results are consistent with the predictions of patient-feeding behavior. Patient-feeding finds additional support in the estimates of coefficients on treatment services. The most significant predictor of both SPECT and PET adoption appears to be whether or not the hospital offers oncology services. Since both SPECT and PET are used heavily in cancer diagnosis, hospitals that offer oncology treatment have a greater incentive to adopt both technologies. Furthermore, the coefficients on cardiac intensive care and cardiac catheterization laboratory (CCL) in SPECT profitability are also significant, supporting the contention that SPECT service feeds patients into cardiology treatment services.

The coefficients on hospital characteristics that provide exogenous asymmetry to the adoption game among rivals are also significant. The estimated coefficients on outpatient visits and bed size in SPECT profitability are also positive, indicating that larger hospitals are more likely to adopt SPECT. The effect of hospital size on PET adoption is less clear: bed size appears to positively affect adoption whereas outpatient visits negatively so.

Non-profit status has a significant, negative effect on SPECT profitability. Furthermore, community hospitals are significantly less likely to adopt SPECT even compared to other non-profit hospitals. Neither indicator appears to have a significant effect on PET profitability.

The coefficients on the market characteristics are overall less significant than those on the hospital characteristics. Hospitals in markets with higher HMO penetration are significantly less likely to adopt SPECT technology; however, no such effect appears with regard to PET technology.

The imprecision of the estimates of the parameters on technology-specific unobserved heterogeneity make interpretation difficult. The estimated values appear reasonable; however, the standard errors are rather large.

Overall, the estimates best support patient-feeding as being the primary motivation for adoption of these technologies. The presence of relevant treatment services appears to be the best predictor of whether or not a hospital adopts either SPECT or PET. Furthermore, an increase in the number of hospitals has the effect that this behavior would predict. Namely, adding a hospital to the market decreases the profitability of the individual technologies, but increases the profit complementarity between them.

The overall goodness of fit is rather good. The likelihood ratio test statistic for the hypothesis that all parameters except the constants and unobserved heterogeneity parameters are restricted to zero is 257.16, which is large even for the thirty-six degrees of freedom in the test statistic.

6 Discussion

6.1 Bias from Neglecting Changes in Complementarity

While estimation of the effect of market structure on profit complementarity is of interest to economists in itself, one should also take this effect into account even when one desires to estimate only the level of complementarity between two decisions. Clearly, if market structure systematically affects profit complementarity, then an estimate of the level that neglects this factor will be rather sensitive to the market structures present in a sample. Suppose that we were interested in estimating only the level of profit complementarity between SPECT and PET in order to infer the strength of the self-cannibalization effect present when offering both services. Samples that over-represent monopoly hospital markets would lead us to overestimate the strength of this self-cannibalization because it neglects the reduction in self-cannibalization brought about by the presence of rivals. By accounting for the change in profit complementarity, the inferences are more robust to the distribution of market structures in the sample.

Furthermore, neglect of changing profit complementarity will lead to biased estimates of the strategic coefficients, which are often of great interest in entry or adoption contexts. To see this, consider an expansion of the profit equation for the dual-adoption option from (7):

$$\pi_3(x_i, P_{-i}, \nu^i) = (\alpha_1 + \alpha_2 + \alpha_3) + x_i'(\beta_1 + \beta_2) + y_i'(\delta_1 + \delta_2 + \delta_3) + (\nu_1^i + \nu_2^i) + \varepsilon_3$$

where $y_i \equiv \big(E\big[\ln(1+r_1^i)\big|P_{-i}\big],\, E\big[\ln(1+r_2^i)\big|P_{-i}\big]\big)'$ and $\delta_j = (\delta_{j1}, \delta_{j2})'$ for $j = 1, 2, 3$. Now imagine omitting $y_i'\delta_3$ from the specification. If the two parameters in δ_3 are positive, then the omission will induce positive correlation between the rival adoption expectation terms and the error term for this option, which would be $\tilde{\varepsilon}_3 = \varepsilon_3 + y_i'\delta_3$. The omissions in this case will bias upward the estimators for the coefficients on the rival adoption expectation terms in the SPECT and PET profitability equations ($\hat{\delta}_1$ and $\hat{\delta}_2$). The strength of this bias will increase with the proportion of observations that adopt both technologies. If the true parameters in δ_1 and δ_2 are all negative, then the bias will bring the estimates in $\hat{\delta}_1$ and $\hat{\delta}_2$ closer to zero and may lead us to believe that the hospitals are more isolated from each other than they really are and that the two technologies are more differentiated from each other than they really are. If δ_1 and δ_2 are really positive, because of a medical arms race effect for example, then the bias will lead us to believe this the arms race effect is stronger than it actually is.

In fact, even if one is interested only the adoption of one of the technologies, the neglect of changes in profit complementarity may result in biased estimates. Suppose that we want

Table 2: Parameter Estimates from NPL Estimation

Variable	SPECT	PET	Γ
Constant	-1.731	-0.164	0.928
	(3.268)	(6.724)	(0.546)
Exp. SPECT competition	0.935	0.169	1.302
	(0.383)	(1.302)	(1.567)
Exp. PET competition	-0.475	-0.620	0.121
	(1.540)	(6.207)	(7.358)
Number of hospitals	-0.692	-0.692	1.662
	(0.169)	r	(0.476)
Oncology	2.137	0.986	
	(0.126)	(0.346)	
Cardiac IC	0.539		
	(0.108)		
Open heart surgery	0.288		
	(0.231)		
CCL	0.313		
	(0.144)		
Angioplasty	0.611		
	(0.222)		
Beds	0.505	0.521	
	(0.100)	(0.196)	
Outpatient visits	0.887	-0.357	
	(0.083)	(0.149)	
Non-profit hospital	-0.372	-0.119	
	(0.176)	(0.348)	
Community hospital	-0.735	0.267	
	(0.128)	(0.262)	
Teaching hospital	-0.227		
	(0.346)		
Population	0.136	0.034	
	(0.090)	(0.167)	
Median income	-1.332	-0.273	
	(0.315)	(0.653)	
Medicare penetration	-1.152	-2.509	
	(1.911)	(4.421)	
HMO penetration	-1.253	-0.126	
	(0.476)	(0.988)	
Unobserved Heterogeneity	σ_1	σ_2	ρ
	3.630	1.025	0.716
	(6.191)	(4.523)	(8.389)
Observations	2011		
Log-likelihood	-1595.8		
LRI	257.16		

Notes: The variables bed size, outpatient visits, population, median income, and number of hospitals are measured included in log form. The "SPECT" and "PET" columns denote the respective individual profitability equations and the "Γ" column denotes the profit complementarity equation. Standard errors are in parentheses.

only to estimate the parameters that enter the PET adoption decision. If we assume, in contrast to the rest of the paper, that the decision to adopt SPECT technology is exogenous to the PET adoption decision, we may model the PET adoption decision as a binary choice logit with the payoff to adoption ($a_{i2} = 1$) derived from the main specification in (7):

$$\tilde{\pi}_{i1} = \alpha_2 + x_i'\beta_2 + \delta_{21}\ln(1+r_1^i) + \delta_{22}E\big[\ln(1+r_2^i)\big|P_{-i}\big] + \alpha_3 a_{i1} + \delta_{31}a_{i1}\ln(1+r_1^i) + \delta_{32}a_{i1}E\big[\ln(1+r_2^i)\big|P_{-i}\big] + \tilde{\varepsilon}_{i1} \quad (14)$$

where $a_{i1} \in \{0,1\}$ is the indicator of SPECT adoption and where $\tilde{\varepsilon}_{i1}$ is a logistic error. Note that we drop the unobserved heterogeneity term ν_1^i because it is redundant when estimating only a single adoption decision. Suppose that we neglected the terms associated with changes in profit complementarity and instead specified the payoffs to adoption as:

$$\tilde{\pi}_{i1}' = \alpha_2 + x_i'\beta_2 + \delta_{21}\ln(1+r_1^i) + \delta_{22}E\big[\ln(1+r_2^i)\big|P_{-i}\big] + \alpha_3 a_{i1} + \tilde{\varepsilon}_{i1} \quad (15)$$

The specification in (15) accounts somewhat for profit complementarity between the two technologies by its inclusion of the SPECT indicator. However, by omitting the other terms, we again induce bias in the estimators for δ_{21} and δ_{22}. If profit complementarity is increasing with rival adoption of PET ($\delta_{32} > 0$), then the estimator of δ_{22} will be biased upward. Again, this bias will become stronger as a larger portion of those hospitals that adopt PET have also adopted SPECT. For our sample, this proportion is very large and hence the estimator for δ_{32} will have a mean close to $\delta_{22} + \delta_{32}$. Note that the bias here is not limited to the finite samples: the omission will cause the estimators to be inconsistent as well.

6.2 Extensions and Policy Implications

We have focused on demonstrating how profit complementarity among a firm's decisions is influenced by the market structure under which it operates. This analysis is only a first step; however, it highlights a feature of multi-product oligopolies that has previously been neglected. We consider now avenues where future research may use these ideas to contribute further to the study of imperfect competition.

While we have modeled adoption using a static approximation to a repeated game among firms, the effect of market structure on profit complementarity has implications for a dynamic game of technological adoption. In a dynamic game, not only will the decisions *whether* to adopt the technologies jointly or separately be affected by the competitive environment, but the decisions *when* to adopt them will as well. Consider the case of service-oriented technologies like SPECT and PET. A firm facing no rivals in either submarket may have an incentive to adopt one technology and wait on adopting another until its acquisition cost falls below a threshold where the second adoption is profitable. This threshold will take into consideration the self-cannibalization of revenues from the first technology. If a rival adopts the first technology as well, then the reduction in potential self-cannibalization may induce the firm to adopt the second technology earlier than it otherwise would. More adoption of one technology would spill over into more (or at least quicker) adoption of the other, even though the technologies provide substitutable services. As a consequence, we may witness different diffusion patterns among the technologies across markets with varying competitive structures.

That market structure affects profit complementarity among adoption decisions also provides a further link between competition policy and technological diffusion. Policies that stimulate adoption of one technology by competing firms will also stimulate adoption of substitutable technologies, so long as price competition among adopters is not too intense. In the health care industry, policymakers often worry about adoption of duplicative technologies. While SPECT and PET each have clear advantages over each other for specific diagnostic purposes, concern over redundancy arises because of the large overlap in their usage (as well as the high cost of PET). If the policy goal were to avoid joint adoption in these technologies, then the relative permissiveness of antitrust enforcement to hospital mergers may be further justified by this end. By reducing the set of potential rivals, hospital consolidation may reduce the incentive to joint adoption by ensuring that the self-cannibalization effect will remain strong. On the other hand, the same end may potentially be reached through policies that intensify price competition among hospitals. For example, policies conducive to greater HMO penetration may serve this end. While one should doubt that hospitals will act as aggressively as in the Bertrand example presented, it is conceivable that with high HMO penetration, hospitals may compete in prices aggressively enough so that rival entry actually exacerbates the self-cannibalization from joint adoption.

Beyond technological adoption, the framework presented here is useful for models of spatial competition and market entry. Firms that consider entry into multiple nearby markets face self-cannibalization prospects that may be ameliorated by cross-firm cannibalization from rival entry. While we have limited our attention to two submarkets for simplicity, the framework and intuition carry over to the larger choice sets that would likely be present in spatial contexts. The decomposition introduced by Gentzkow (2005) for multivariate discrete choice payoffs is valid for an arbitrary number of component choices; however, the number of terms grows substantially as the number of component choices increases. One could reduce the dimensionality by imposing distance bands, as in Seim (2004), so that all submarkets within a particular radius have the same coefficients. That we would be able to consider centrally managed entry decisions by multi-market firms provides a promising application of our approach.

7 Conclusion

This paper has investigated the effect of market structure on profit complementarity in the context of adoption of substitutable service-oriented technologies. Factors influencing these changes include the degree of price competition among firms and the substitutability of services. We first outlined a framework for analyzing profit complementarity in a technological adoption or market entry context. We then examined how rival adoption can increase profit complementarity when no pricing strategies exist. On the other hand, very intense price competition among firms, as in a Bertrand setting, will lead to decreasing profit complementarity from rival adoption. That rival adoption of one technology may decrease the potential for self-cannibalization from joint adoption provides an important source of increasing profit complementarity; however, whether rival entry has this effect depends on the intensity of price competition among firms.

To test whether profit complementarity changes based on rival adoption decisions, we looked to the case of SPECT and PET diagnostic imaging technologies. We tested this model on data of hospitals' decisions to adopt these imaging technologies. We estimated a model of joint adoption of the two technologies in an oligopolistic setting, allowing for technology specific heterogeneity and strategic interaction among hospitals. Given possible patient-feeding motives in provision of these services, we also looked for the effect of the number of hospitals in the market on adoption decisions.

The results support patient feeding as the primary concern in the adoption of these technologies. The number of hospitals in the market decreases the profitability of adoption of the individual technologies and increases the profit complementarity between the adoption decisions. Furthermore, hospitals with related treatment services are significantly more likely to adopt either technology. In contrast, expected rival adoption of the technologies does not appear to have a significant effect on the adoption decisions.

Previous studies of multiple technological adoption decisions have treated the complementarity among adoption decisions as constant. The primary contribution of this paper is in demonstrating how models of oligopoly competition would predict different levels of profit complementarity for different market environments. While we have focused our attention on service-oriented technologies, where the associated services are viewed as substitutes by consumers, analogous effects of market structure on profit complementarity should be generated in other contexts.

A Derivations and Examples

A.1 Profit Complementarity Decomposition

Let variable production costs for firm i when it produces q_1^i of service 1 and q_2^i of service 2 be given by $C^i(q_1^i, q_2^i)$, where $C^i(0,0) = 0$. The firm incurs fixed costs of $F^i(a^i)$ from its adoption decision. The costs in F^i include both actual costs of adoption and any unsunk fixed costs in production of the associated service. Note that these fixed costs are assumed not to depend on rival decisions. We specify fixed costs as $F^i((0,0)) = 0$, $F^i((1,0)) = F_0^i + F_1^i$, $F^i((0,1)) = F_0^i + F_2^i$, and $F^i((1,1)) = F_0^i + F_1^i + F_2^i$, where all terms are nonnegative. Note that F_0^i represents a shared component of adoption costs that the firm occurs only once when adopting one or both technologies. This shared adoption cost becomes an important source of profit complementarity, whereas the technology-specific adoption costs F_1^i and F_2^i cancel out in the determination of profit complementarity.

Let $p_j^i(a^i, a^{-i})$ and $q_j^i(a^i, a^{-i})$ be firm i's price and quantity of service $j = 1, 2$ in the equilibrium of the subgame generated by the adoption decisions (a^i, a^{-i}). If firm i does not adopt the technology for service j, then clearly it produces none of that service, and hence $q_1^i\big((0,1), a^{-i}\big) = q_2^i\big((1,0), a^{-i}\big) = 0$. Firm profits in the equilibrium of the (a^i, a^{-i}) subgame are then:

$$\begin{aligned}\pi^i(a^i, a^{-i}) = p_1^i(a^i, a^{-i}) \cdot q_1^i(a^i, a^{-i}) + p_2^i(a^i, a^{-i}) \cdot q_2^i(a^i, a^{-i})& \\ - C^i\Big(q_1^i(a^i, a^{-i}), q_2^i(a^i, a^{-i})\Big) - F^i(a^i)&\end{aligned}$$

Let $R_j^i(a^i, a^{-i})$ denote the net revenues earned by firm i from its operations in service j in the equilibrium of the (a^i, a^{-i}) subgame. These net revenues account for variable production costs specific to service j; however, they account for neither cost interactions nor adoption costs. These net revenues are defined as:

$$\begin{aligned}R_1^i(a^i, a^{-i}) &= p_1^i(a^i, a^{-i}) \cdot q_1^i(a^i, a^{-i}) - C^i\big(q_1^i(a^i, a^{-i}),\ 0\big) \\ R_2^i(a^i, a^{-i}) &= p_2^i(a^i, a^{-i}) \cdot q_2^i(a^i, a^{-i}) - C^i\big(0,\ q_2^i(a^i, a^{-i})\big)\end{aligned}$$

Note that even with adoption of both technologies, the variable costs in $R_1^i((1,1), a^{-i})$ are evaluated with the quantity of the second service set at zero (and analogously for

$R_2^i((1,1),a^{-i}))$. This feature allows for easier comparison of these service-specific net revenues across decision profiles. We account for cost interactions with an economies of scope term SC^i defined below.

The profits to specialized adoption reduce to $\pi^i\big((1,0),a^{-i}\big) = R_1^i\big((1,0),a^{-i}\big) - F_1^i - F_0^i$ and $\pi^i\big((0,1),a^{-i}\big) = R_2^i\big((0,1),a^{-i}\big) - F_2^i - F_0^i$. Profit complementarity is then decomposed as:

$$\Gamma^i(a^{-i}) = \Delta R_1^i(a^{-i}) + \Delta R_2^i(a^{-i}) + SC^i(a^{-i}) + F_0^i$$

where

$$\begin{aligned}
\Delta R_1^i(a^{-i}) &\equiv R_1^i\big((1,1),a^{-i}\big) - R_1^i\big((1,0),a^{-i}\big) \\
\Delta R_2^i(a^{-i}) &\equiv R_2^i\big((1,1),a^{-i}\big) - R_2^i\big((0,1),a^{-i}\big) \\
SC^i(a^{-i}) &\equiv -\Big[C^i\big(q_1^i((1,1),a^{-i}),\ q_2^i((1,1),a^{-i})\big) \\
&\qquad\qquad - C^i\big(q_1^i((1,1),a^{-i}),\ 0\big) - C^i\big(0,\ q_2^i((1,1),a^{-i})\big)\Big]
\end{aligned}$$

Note that the term $SC^i(a^{-i})$ is defined so that economies of scope in variable costs will contribute positively to profit complementarity.

A.2 Details for Example 2.3.1

We demonstrate the result for the case of two firms and note that the argument extends easily to the case of three or more firms. We denote the two firms as A and B and consider the profit complementarity faced by firm A.

Assume that the cost functions of both firms exhibit constant marginal costs and no economies of scope or fixed costs. Assume further that the price of each service from each firm is invariant to the adoption decisions of the firms. We have then that if a firm adopts the technology for service $j = 1, 2$, it receives an average profit of $\varphi_j^i = p_j^i - c_j^i$, regardless of quantity. We restrict attention to the case where each price is set above the corresponding marginal cost so that $\varphi_j^i > 0$.

Let $A1$ denote the option to buy service 1 from firm A and let $A2$, $B1$, and $B2$ represent the analogous options. Let 0 denote the option not to consume any service. When both firms adopt both technologies, then the consumers face the budget set $\{0, A1, A2, B1, B2\}$. Under other adoption decisions, consumers face a nonempty subset of this budget set, where option 0 is always present.

Let $q_j^i(a^A, a^B)$ denote the quantity demanded of service j from firm i when consumers are presented the budget set generated by the adoption decisions (a^A, a^B). The profits to firm i under the adoption decisions (a^A, a^B) can be expressed:

$$\pi^i(a^A, a^B) = \varphi_1^i \cdot q_1^i(a^A, a^B) + \varphi_2^i \cdot q_2^i(a^A, a^B) = R_1^i(a^A, a^B) + R_2^i(a^A, a^B)$$

Using the decomposition of profit complementarity in Equation (2), we have that the self-cannibalization faced by A with respect to the first service as:

$$\Delta R_1^A(a^B) = \varphi_1^A \cdot \Big[q_1^A\big((1,1),a^B\big) - q_1^A\big((1,0),a^B\big)\Big]$$

Consider the bracketed difference term: that is, the difference in quantity demanded of service 1 when A provides both services and when A provides only service 1, given B's adoption choices. By offering both services, firm A expands the choice set of consumers by adding to it $A2$. All consumers who would choose $A1$ when $A2$ is also available would also choose $A1$ when $A2$ is not available, assuming that preferences satisfy the independence axiom. Hence, firm A can not increase the quantity demanded of service 1 by offering service 2 as well. For the quantity demanded to decrease requires only that there is at least one consumer who prefers $A2$ to $A1$, but prefers $A1$ to 0 and to any service offered by firm B under a^B. So long as there is at least one such consumer, and so long as $\varphi_1^A > 0$, we have that $\Delta R_1^A(a^B) < 0$. The analogous argument shows that $\Delta R_2^A(a^B) \leq 0$ and that the inequality is strict if there is at least one consumer that prefers $A1$ to $A2$ and $A2$ to other options in the budget set. Therefore, if either of these consumer types exist, then we have:

$$\Gamma^A(a^B) = \Delta R_1^A(a^B) + \Delta R_2^A(a^B) < 0$$

To see that A's profit complementarity increases as B adopts more technologies, compare $\Gamma^A(1)$ to $\Gamma^A(0)$. We have:

$$\Delta R_1^A((1,0)) - \Delta R_1^A((0,0)) = \varphi_1^A \cdot \left[\left[q_1^A\big((1,1),(1,0)\big) - q_1^A\big((1,0),(1,0)\big)\right] - \left[q_1^A\big((1,1),(0,0)\big) - q_1^A\big((1,0),(0,0)\big)\right]\right]$$

The second difference, $q_1^A\big((1,1),(0,0)\big) - q_1^A\big((1,0),(0,0)\big)$, is composed of those consumers with preferences that satisfy $A2 \succ A1 \succ 0$. The first difference is composed of those consumers with preferences that satisfy $A2 \succ A1 \succ 0$, and $A1 \succ B1$. Notice that the second group of consumers contains the first, and hence $\Delta R_1^A((1,0)) - \Delta R_1^A((0,0)) \geq 0$. If there is at least one consumer for whom $A2 \succ B1 \succ A1 \succ 0$, then the first difference is strictly smaller in absolute value than the second, and therefore $\Delta R_1^A((1,0)) - \Delta R_1^A((0,0))$ is strictly positive. By the analogous argument, $\Delta R_2^A((1,0)) - \Delta R_2^A((0,0))$ is nonnegative, and is strictly positive if there exists at least one consumer for whom $A1 \succ B1 \succ A2 \succ 0$. We then have that $\Gamma^A((1,0)) - \Gamma^A((0,0)) \geq 0$, where the inequality is strict if at least one of the consumers types discussed are present.

Similar reasoning shows that the complementarity differences $\Gamma^A((0,1)) - \Gamma^A((0,0))$, $\Gamma^A((1,1)) - \Gamma^A((1,0))$, and $\Gamma^A((1,1)) - \Gamma^A((0,1))$ are all nonnegative and that sufficient heterogeneity in consumer preferences would make them positive. Note, however, that additional restrictions would be necessary to establish the sign of $\Gamma^A((0,1)) - \Gamma^A((1,0))$.

A.3 Details for Example 2.3.2

While consumers have heterogeneous preferences over services, they view firms providing a particular service as homogeneous. To keep the example tractable, we model product differentiation between the two services via the linear city with linear travel costs. We fix the locations of the two services at the endpoints of the city, whose length is normalized to unity. If both firms offer a service, all consumers purchase from the one offering the lower price. Demand is split evenly if the firms offer the same price. The consumer at location $x \in [0,1]$ that faces market prices (p_1, p_2) for the two services receives the following net utilities from purchasing one unit of the services:

$$u_1(x, p_1, p_2) = v_1 - p_1 - \tau x \qquad\qquad u_2(x, p_1, p_2) = v_2 - p_2 - \tau(1 - x)$$

where $v_1 > 0$ and $v_2 > 0$ are the consumers' valuations of the services if there were no travel costs and where $\tau > 0$ is the marginal disutility of travel to consumers. We reiterate that the heterogeneity here is in the two types of services, not in the firms.

Firms again have no fixed costs and constant marginal costs, and we assume that these costs are identical over firms for a given service; however, they may differ across the two services. Since we allow the two services to have different valuations, we normalize the costs to zero and interpret the valuations and equilibrium prices as net of marginal costs. The results presented here are robust to the inclusion of positive marginal costs so long as these costs do not exceed the valuations of the services.

We deal only with the case where travel costs are not so high relative to the valuations that the two service markets are effectively isolated. However, we assume that travel costs are high enough so that a monopolist, having adopted both technologies, would not want to cover the market with only one of the services. We satisfy both these conditions by restricting the travel cost to the range $\left|v_1 - v_2\right| < \tau < \frac{1}{2}\left[v_1 + v_2\right]$. We also assume that $\tau > \frac{1}{2}v_1$ and $\tau > \frac{1}{2}v_2$ to avoid multiple forms of the equilibrium profit functions; however, these are technical restrictions that do not affect the qualitative results.

The consumer at location $x \in [0,1]$ that faces market prices (p_1, p_2) for the two services receives the following net utilities from purchasing one unit of the services:

$$u_1(x, p_1, p_2) = v_1 - p_1 - \tau x \qquad\qquad u_2(x, p_1, p_2) = v_2 - p_2 - \tau(1 - x)$$

Let $p_1^A(a^A, a^B)$ denote firm A's price of service j in the equilibrium of the subgame generated by the adoption decisions (a^A, a^B). If firm A adopts only the first technology and B does not adopt either technology, then A will charge a price of $p_1^A\big((1,0),(0,0)\big) = \frac{1}{2}v_1$ and will earn profits of $\pi^A\big((1,0),(0,0)\big) = v_1^2/(4\tau)$. Likewise, if A adopts only the second technology and B adopts neither, then $p_2^A\big((0,1),(0,0)\big) = \frac{1}{2}v_2$ and $\pi^A\big((0,1),(0,0)\big) = v_2^2/(4\tau)$. If A adopts both technologies and B adopts neither, then with travel costs in the assumed range, the monopolist will serve the entire market and will sell positive quantities of both services. We have $p_1^A\big((1,1),(0,0)\big) = \frac{3}{4}v_1 + \frac{1}{4}v_2 - \frac{1}{2}\tau$, $p_2^A\big((1,1),(0,0)\big) = \frac{3}{4}v_2 + \frac{1}{4}v_1 - \frac{1}{2}\tau$, and $\pi^A\big((1,1),(0,0)\big) = \frac{1}{2}(v_1 + v_2 - \tau) + (v_1 - v_2)^2/(8\tau)$. The profit complementarity faced by the monopolist is then:

$$\Gamma^A((0,0)) = \frac{-(2\tau - v_1 - v_2)^2}{8\tau} \tag{16}$$

Now suppose that B adopts the first technology. If A adopts only the the first technology, then the Bertrand result will prevail: price will be driven down to marginal cost, or zero in this case. Hence, we have $\pi^A\big((1,0),(1,0)\big) = 0$. If A adopts only the second technology, then the Hotelling duopoly equilibrium results. We have $p_2^A\big((0,1),(1,0)\big) = \tau + \frac{1}{3}(v_2 - v_1)$ and $\pi^A\big((0,1),(1,0)\big) = (3\tau + v_2 - v_1)^2/(18\tau)$.

If A adopts both technologies and B adopts only the first, then one may question whether A's incentive to out-bid B in the price of service 1 is as strong as if A were providing only that service. Even though A is aware of the substitution effect that a price war in the first service will have on its service 2 business, it will still compete as a Bertrand competitor in service 1 if it has already adopted that technology. To see this, consider any candidate equilibrium where $0 < p_1^B < p_1^A$: that is, where B charges a lower service 1 price than does A and hence captures the entire market demand for service 1. By undercutting p_1^B by an infinitesimal amount, as in the standard Bertrand model, firm A will steal the demand for service 1 without effectively changing the relative market prices of the two services, and hence not affecting the demand for service 2. So long as $p_1^B > 0$, A has an incentive to undercut B's price, regardless of whether or not A also offers the second service. We therefore have $p_1^A\big((1,1),(1,0)\big) = 0$. Given this result, the pricing decision for the second service may take the equilibrium price of the first service as exogenous. We then have that $p_2^A\big((1,1),(1,0)\big) = \frac{1}{2}(\tau + v_2 - v_1)$ and $\pi^A\big((1,1),(1,0)\big) = (\tau + v_2 - v_1)^2/(8\tau)$. The profit complementarity faced by A when B adopts the first technology is therefore:

$$\Gamma^A((1,0)) = \frac{5(v_2 - v_1)^2}{72\tau} - \frac{v_2 - v_1}{12} - \frac{3\tau}{8} \tag{17}$$

From Equations (16) and (17), we derive the change in profit complementarity as:

$$\Gamma^A((1,0)) - \Gamma^A((0,0)) = \frac{7v_1}{12} + \frac{5v_2}{12} - \frac{7\tau}{8} - \frac{v_1^2}{18\tau} - \frac{v_2^2}{18\tau} - \frac{7v_1v_2}{18\tau} \tag{18}$$

Transforming Equation (18) into a quadratic in τ, we can see that the parabola opens downward. Inspection of the quadratic shows that it becomes positive for some τ only if v_1 is very large relative to v_2 (or the reverse if $\Gamma^A((0,1)) - \Gamma^A((0,0))$ is analyzed).[14] Even where this is true, visual inspection has failed to locate cases where the positive portion overlaps with the range of τ for which the derivations are valid. At least for cases where the two service valuations are in the same ballpark, profit complementarity decreases with rival adoption.

A.4 Details for Example 2.3.3

For simplicity, we assume that hospitals care only about indirect profits from feeding patients into treatment services and do not value direct profits from diagnostic service provision. The combination of this case with that of Example 2.3.1 is straightforward and generates the same qualitative results.

Suppose that there are n hospitals in the hospital market that provide treatment services for a particular disease for which SPECT and PET are appropriate diagnostic technologies (e.g. non-pulmonary lung cancer). All hospitals provide both diagnostic and treatment services for this disease, even if they do not adopt SPECT or PET.[15] However, a hospital that has a SPECT or PET facility is able to attract more patients for diagnosis. We assume that patients are more likely to consume treatment service from a hospital if they were diagnosed at that hospital than if they were not.

Let $q_j^i\big(a^i, a^{-i}, n\big)$ denote the quantity of patients that elect to use hospital i's SPECT ($j = 1$) or PET ($j = 2$) diagnostic service in the equilibrium under the adoption profile (a^i, a^{-i}). Note that unlike in the previous examples, we allow the equilibrium quantities to depend on the number of hospitals in the market, not just the adoption decisions. Since all hospitals provide at least a primitive diagnostic service, patients in markets with more hospitals have more diagnostic options, so we assume that $q_j^i\big(a^i, a^{-i}, n+1\big) \le q_j^i\big(a^i, a^{-i\prime}, n+1\big)$.[16]

Let $\psi_j^i(n)$ denote the expected profit in treatment service for each patient scanned by i's SPECT or PET machine. This expected per-patient treatment profit accounts for the probability that a scanned patient is diagnosed with the disease, the probability that the diagnosed patient returns to i for treatment, and the profit to i from the patient's use of its treatment service. Note that this term depends on the number of hospitals in the market, but does not depend on adoption decisions. In particular, we assume that $\psi_j^i(n+1) < \psi_j^i(n)$ for all $n \in \mathbb{N}$. As the number of hospitals in the market increases, diagnosed patients have

[14] Specifically, in order for the parabola to have real roots, we must have $v_1(v_1 - 42v_2) > v_2^2$, which necessitates that v_1 be much larger than v_2.

[15] One can suppose that all hospitals have a less effective diagnostic technology for the disease, such as a CT scanner.

[16] If the inequality holds when the additional hospital does not adopt either technology, then it holds for all decisions of that hospital.

more treatment options and hence the probability that a diagnosed patient will return to i for treatment diminishes. Furthermore, the additional competition in the treatment service market may lower the profits from the patient's use of i's treatment service.

Since we have assumed that all hospitals provide at least a basic diagnostic service, let $q_0^i\big(a^i, a^{-i}, n\big)$ and $\psi_0^i(n)$ respectively denote the quantity demanded and expected per-patient profit for this basic diagnostic service. We assume for simplicity that the quantity demanded and expected per-patient profit for this basic diagnostic service are small enough relative to those of SPECT and PET that the indirect profits from this basic service can safely be ignored in the following analysis.

The self-cannibalization effect for SPECT in this situation is given:

$$\Delta R_1^i(a^{-i}, n) = \psi_1^i(n)\Big[q_1^i\big((1,1), a^{-i}, n\big) - q_1^i\big((1,0), a^{-i}, n\big)\Big]$$

and the self-cannibalization effect for PET is given analogously. Note that for a fixed n, the effect of additional rival adoption on ΔR_j^i follows that described in Example 2.3.1. We will therefore have that additional rival adoption increases profit complementarity for the same reason as in that example. Here, however, we are more interested on the effect of increasing the number of hospitals in the market. This effect on SPECT cannibalization is given:

$$\begin{aligned}
&\Delta R_1^i(a^{-i\prime}, n{+}1) - \Delta R_1^i(a^{-i}, n)\\
&\quad = \psi_1^i(n{+}1)\Big[q_1^i\big((1,1), a^{-i\prime}, n{+}1\big) - q_1^i\big((1,0), a^{-i\prime}, n{+}1\big)\Big]\\
&\quad - \psi_1^i(n)\Big[q_1^i\big((1,1), a^{-i}, n\big) - q_1^i\big((1,0), a^{-i}, n\big)\Big]
\end{aligned}$$

Pivoting the right-hand side, we have:

$$\begin{aligned}
&\Delta R_1^i(a^{-i\prime}, n{+}1) - \Delta R_1^i(a^{-i}, n) \qquad (19)\\
&\quad = \Big[\psi_1^i(n{+}1) - \psi_1^i(n)\Big]\cdot\Big[q_1^i\big((1,1), a^{-i\prime}, n{+}1\big) - q_1^i\big((1,0), a^{-i\prime}, n{+}1\big)\Big]\\
&\quad + \psi_1^i(n)\Big\{\Big[q_1^i\big((1,1), a^{-i\prime}, n{+}1\big) - q_1^i\big((1,0), a^{-i\prime}, n{+}1\big)\Big]\\
&\qquad - \Big[q_1^i\big((1,1), a^{-i}, n\big) - q_1^i\big((1,0), a^{-i}, n\big)\Big]\Big\} \qquad (20)
\end{aligned}$$

Since $\psi_1^i(n{+}1) - \psi_1^i(n) < 0$, the first term on the right-hand side is positive. The difference in differences inside the curly brackets can be shown to be positive as well with sufficient heterogeneity in patient preferences by the same logic as in Example 2.3.1. Since this same effect can be demonstrated for ΔR_2^i, we have that profit complementarity is increasing in n, as well as in rival adoption.

The intuition for this result is slightly different than that for Example 2.3.1. In the previous example, the source of increasing complementarity came from rival cannibalization of quantity that decreased the potential for self-cannibalization of quantity. A similar quantity effect is present here as well, given by the second term in (19). However, an additional source of increasing complementarity stems from the devaluing of the self-cannibalization of quantity. Since an increase in the number of hospitals decreases the expected per-patient profit, the self-cannibalized quantity is not only reduced, but each patient in this quantity is worth less as well.

B Estimation Details

B.1 Consistency of the NPL Estimator

Let $\ln \mathscr{L}_n^P$ be the pseudo-likelihood function for a sample of n observations and let $\ln \mathscr{L}_\infty^P$ be the limiting counterpart as $n \to \infty$. The estimator $(\hat{\theta}_n, \hat{P}_n)$ converges to an estimator $(\bar{\theta}, \bar{P})$ that satisfies the following properties. First, $\bar{\theta} \in \text{argmax}_{\theta \in \Theta} \ln \mathscr{L}_\infty^P(\theta, \bar{P})$. Secondly, $\bar{P} = \Psi(\bar{P}; \bar{\theta})$. Finally, $\ln \mathscr{L}_\infty^P(\bar{\theta}, \bar{P}) \geq \ln \mathscr{L}_\infty^P(\theta, P)$ for all (θ, P) that satisfy the first two properties. Note that the true parameters and choice probabilities (θ^*, P^*) satisfy these three properties. Furthermore, the true parameters and choice probabilities are the only ones that satisfy these three properties. Too see this, suppose $(\bar{\theta}, \bar{P}) \neq (\theta^*, P^*)$. If $\bar{P} = P^*$, then by Assumption 3, $\bar{\theta} = \theta^*$ because P^* is an equilibrium only under θ^*. Hence, $(\bar{\theta}, \bar{P}) \neq (\theta^*, P^*)$ necessitates that $\bar{P} \neq P^*$. The Kullback-Leibler Information Inequality then implies that $\ln \mathscr{L}_\infty^P(\bar{\theta}, \bar{P}) < \ln \mathscr{L}_\infty^P(\theta^*, P^*)$. Hence, even if $(\bar{\theta}, \bar{P})$ satisfy the first two properties, they will not satisfy the last.

B.2 Implementation of the NPL Method

B.2.1 Equilibrium Search

Given a parameter vector θ and sample characteristics X, we find an equilibrium for each market l using the method of successive approximations. To reduce the chance that the search bounces between choice probabilities without settling on an equilibrium, we iterate through the firms in a market and immediately update the best response choice probabilities of each firm for use in the best response computation of later firms in the sequence. The approach is analogous to the Gauss-Seidel method for solving systems of linear equations.

With a market of n firms with characteristics given by X^l, we initialize the choice probabilities with those resulting from the search during the previous NPL iteration. With these choice probabilities $P_{0,0}^l$, we compute the first firm's best response choice probabilities as $p_{0,1}^i = \psi(P_{-i,0,0}^l; x_i, \theta)$ and replace firm i's entries in $P_{0,0}^l$ with those from $p_{0,1}^i$ to get $P_{0,1}^l$. We then do the same for each subsequent firm, again updating the choice probabilities as soon as new guesses are available. After completing the sequence of firms, we have $P_{1,0}^l$ as the new candidate equilibrium. If the change in choice probabilities falls within the desired tolerance, then we use $P_{1,0}^l$ as the equilibrium. If not, then we repeat the procedure until such convergence is achieved.

While we have found aberrant cases where the search did not converge, the method overall provides a reliable means of locating a market equilibrium. Of course, neither this method nor any other search method guarantees that the equilibrium found is unique.

B.2.2 Computation of Expectations

Given rival choice probabilities P_{-i} for a firm with n rivals, we need to compute the expected log number of entrants that the firm expects in each submarket. For each rival, we first transform the choice probabilities over the four bundles into simple Bernoulli probabilities of entry into each submarket. Let p_1^k denote rival k's probability of entering the first submarket. The density function of the random variable r giving the number of rivals that firm i would face in the first submarket is that of a sum of independent but heterogeneous Bernoulli random variables. The density function is given by:

$$\Pr\{r_1 = m\} = \sum_{a^1=0}^{1} \cdots \sum_{a^n=0}^{1} 1\Big\{\textstyle\sum_{k=1}^n a^k = m\Big\} \prod_{k=1}^n (p_1^k)^{a^k} (1 - p_1^k)^{1-a^k}$$

where $1\{\cdot\}$ is the indicator function.

With this density computed, the expected log number of firms operating in the first submarket (conditional on firm i operating in that submarket) is simply:

$$E\big[\ln(1+r_1)\big] = \sum_{m=0}^{n} \Pr\{r_1 = m\} \ln(1+r_1)$$

B.2.3 Monte Carlo Integration

In both the equilibrium search and the evaluation of the log-likelihood function, the integral in (8) is computed via simulation. To simulate the integral, we need to draw S realizations of the random variables (ν_1^i, ν_2^i) for each realization. This pair of random variables follows the bivariate normal distribution with mean zero and covariance matrix:

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_1\sigma_2\rho \\ \sigma_1\sigma_2\rho & \sigma_2^2 \end{pmatrix}$$

Bivariate normal random variables have the convenient property that if u_1 and u_2 are two independent draws from the standard normal distribution, then $(\nu_1, \nu_2)' = \Sigma^{1/2}(u_1, u_2)'$, where $\Sigma^{1/2}$ is the Cholesky root of the covariance matrix, will follow the desired bivariate normal distribution.

To implement the simulation, we replicate each observation S times and augment its characteristics matrix with two columns, filled with independent draws from the standard normal distribution. The coefficients on these characteristics will be the entries in the Cholesky root of the covariance matrix. Once these coefficients are estimated, we undo the Cholesky decomposition to obtain the estimated standard deviation and correlation parameters. The standard errors on these estimators are computed via the delta method. Note that the standard errors of all parameter estimators are computed using the actual sample size, not the replicated sample size.

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